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Impact of Agricultural Income Shocks due to Extreme Weather Events on the Food Security of the Poor in Central Asia

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The majority of rural households in Central Asia have strong dependence on farming incomes for their livelihoods. Any adverse shocks on agricultural production, for example, through extreme weather events, could have negative consequences on their food security. The analysis of the nationally representative agricultural household surveys using quantile regressions by instrumentalizing for endogeneity between consumption and production decisions confirms that poorer households are more vulnerable to the impacts of farming income shocks. Every 1% decrease in the level of their farming profits is likely to lead to 0.52% decrease in their food expenses. A similar decrease for the richest 10% of agricultural households would translate to only 0.39% decrease in food consumption. Key measures to enhance food security among the poor agricultural households in Central Asia were found to be improving market access and diversifying crop portfolios.

Keywords: Central Asia, poverty, market access, crop diversification

1. Introduction

Agriculture remains a key source of livelihood for a majority of rural households in most of Central Asia. Any shocks to agricultural incomes may have significant repercussions on rural households in the region. Specifically, the impacts of weather shocks on agricultural incomes and rural poverty can be complex. From one hand, any price increases for agricultural commodities caused by weather shocks may reduce producers' income losses or even increase revenues. On the other hand, net food buying rural (and urban) households, especially the poorest ones for whom food is a major expense category, could be hit hard by rising food prices (von Braun et al., 2008). Moreover, households with subsistence-based agricultural activities and residing in areas with lower market access may be negatively affected by lower harvests potentially reducing their food consumption. At the macroeconomic scale, more expensive and scarcer food is also likely to put negative pressures on the rest of the developing economy, weakening industrial and investment competitiveness through higher minimum wages. A key impact of future climate change would likely happen through increased weather extremes and variation. A better knowledge how current weather extremes and variations affect different categories of agricultural households could provide with clues about their reactions to increased weather variability under the climate change as well.

Potential impacts of weather shocks on the livelihoods of rural households need to be studied by fully accounting for different roles of agricultural households as both producers and consumers of agricultural products, as labor suppliers, as well as interactions between these three dimensions. Any such analysis would still be deficient unless it distinguishes weather shock impacts depending on households' resource endowments, with especially careful look at the impacts on poor households. The previous literature has shown that different categories of households may respond differently to the same external shocks, with the poorer households having less resilience and adaptive capacities, thus being more vulnerable to negative shocks (Ahmed, Diffenbaugh, & Hertel, 2009).

This study advances the current literature on the economic impacts of weather shocks on agricultural households and their food security in three ways. First, it estimates the relationship between weather shocks and rural poverty using the agricultural household model framework. Most previous studies on the topic ignore agricultural households' potentially interlinked decision making on production, consumption and labor supply and

thereby their comprehensive adaptation actions. Moreover, even in broader climate change literature although almost each and every study does emphasize the poverty impacts of climate change, mostly this emphasis is based on qualitative judgments rather than quantitative analysis. Secondly, by disaggregating impacts of climate shocks according to different categories of households (poor, middle, rich; net food buyers or sellers) into the standard agricultural household model it distinguishes the impacts of climate change depending on these household characteristics, with emphasis on the poor households. Third, it sheds a spotlight on Central Asia, a region that has so far been very little studied both in terms of responses of agricultural households to external shocks and especially on their reactions to weather and climate shocks. However, the study also has a limitation. It does not explicitly account for different risk attitudes of the households, which usually may play an important role in shaping households' decision making process; hence more future research is needed in this area.

2, Relevant Literature

The relationship between climate and poverty is not straightforward leading to well-known debates about the role of climate and of geography as a whole in determining per capita incomes (Bloom, Sachs, Collier, & Udry, 1998). Mendelsohn, Basist, Kurukulasuriya, & Dinar (2007) posit, based on data from USA and Brazil and reduced form regressions, that climate has statistically significant effect on rural incomes and climate change is likely to increase rural poverty. Thurlow, Zhu, & Diao (2009) find that climate variability costs Zambia 4.3 bln USD over a 10-year period and may keep about an additional 2.3% of the population below the poverty line by 2016. Hertel, Burke, & Lobell (2010) predict that a possible rise in major global staple prices by 10-60% by 2030, could increase the poverty rates for non-agricultural households in parts of Africa and Asia by 20-50%, while agriculture-specialized households elsewhere in Asia and Latin America could actually experience reductions in their poverty rates. Dell, Jones, & Olken (2012) find that higher temperatures substantially reduce economic growth in poor countries, while the same have no statistically significant impact on the growth rates in rich countries. Market failures also limit the ability of agricultural households to cope with risks and external shocks (Fafchamps, 1992).

Climate change is expected to increase the frequency of extreme weather events (IPCC, 2012). Weather shocks are widely considered to be one of the important sources of price volatility (Ahmed, et al., 2009). Increased price volatility for agricultural commodities has long been argued to exacerbate poverty levels, chiefly in poor developing countries (von Braun, et al., 2008). In fact, Ahmed et al. (2009) indicate that climate extremes affect the welfare of poor households negatively, especially rural laborers and urban poor. Ito & Kurosaki (2009) find that faced with weather shocks, agricultural households, especially the smallholder and landless poorer households, seek to increase their off-farm labor supply, especially to non-agricultural activities. Akramov (2011) reports that as a result of food price spikes in 2007, partly caused by negative weather shocks in conjunction with other factors (Mitchell, 2008; von Braun & Tadesse, 2012), USDA's annual food security assessment indicated that in Kyrgyzstan, Tajikistan and Uzbekistan, food consumption for the poorest households fell beyond the nutritional target. More specifically, increases in the price of wheat, sugar, oils and fats during 2010-2011 led to 3.6% net increase in poverty in Tajikistan (Ivanic, Martin, & Zaman, 2012). Nelson et al. (2010) project that climate change may have negative effects on the eradication of child malnutrition in Central Asia.

Major share of poor people in developing countries are located in rural areas and derive their livelihoods from agricultural production. Most of these producers are semi-subsistence smallholders (Ahn, Singh, & Squire, 1981). Over the last 30 years, there have been considerable advances in economic literature within the framework of agricultural household models (AHM) leading to better understanding of incentives and behavior of such smallholder household farms in developing countries (Singh, Squire, & Strauss, 1986). A key feature of agricultural household models is that they allow for making valid inferences when households' production decisions are not separable from their consumption decisions resulting from market imperfections due to high transaction costs (ibid.). Other advantages of AHM include better accounting for such smallholder household characteristics as diversified crop portfolio instead of specialization in one crop and preference to produce staple crops instead of potentially more profitable cash crops (Minot, 2011).

Agricultural household models were first developed by Kuroda & Yotopoulos (1978) to explain the surprising finding that increasing crop prices did not lead to higher marketed surpluses of those crops in Japan (Taylor & Adelman, 2003). The intellectual origins of agricultural household models could be traced back to the works of Chayanov (1929) and (Becker, 1965). If earlier agricultural household models were chiefly concerned with the impacts of agricultural price policies, later on they have also been applied to a very diverse

range of issues such as missing markets and transaction costs (Sadoulet & de Janvry, 1995), off-farm labor supply, technology adoption, nutrition, income distribution, migration, etc., thus, in fact, becoming the key starting point for microeconomic research of agricultural households in developing countries (Singh, et al., 1986; Taylor & Adelman, 2003).

The estimations of AHM are extremely sensitive to assumptions about the integration of the households to product and factor markets, i.e. weather the agricultural household model is separable or non-separable. Therefore, there is a need for testing the separability of the agricultural household model. Several separability tests have been developed, each with its advantages and weaknesses. Vakis, Sadoulet, de Janvry, & Cafiero (2004) classify these separability tests into three categories: 1) global tests not accounting for heterogeneity among households (Benjamin, 1992; Jacoby, 1993). The usefulness of these tests is limited because market failures are usually idiosyncratic, and not covariate (Vakis, et al., 2004). 2) Idiosyncratic tests accounting for heterogeneity across households (Feder, Lau, Lin, & Luo, 1990; Maddala, 1983; Sadoulet, de Janvry, & Benjamin, 1998) (Feder et al. 1990, Maddala 1983, Sadoulet et al.1998). This type of separability tests were used to test for failure in some specific markets or in any market. In cases when the test is used for some specific markets, for example, credit market (Feder, et al., 1990), the problem is that the households that exhibit separable behavior in that specific market tested could actually have non-separable behavior in some other market. The problem with applications to any one market (and thus deducing the household behavior in all markets) lies in conceptual and empirical difficulty of implementation, sensitivity to specifications (Vakis, et al., 2004). 3) Tests that reveal idiosyncratic non-separability on the basis of observed behavior as suggested by Vakis et al. (2004). These tests allow for drawing conclusions on the separability of decision making by heterogeneous households using a reduced form approach, are not confined to one specific market and make use of unknown sample separation.

3. Conceptual Framework

While studying the impacts of weather shocks and climate change on the livelihoods of agricultural households, one needs to adequately account for heterogeneity of agricultural households, including differentiating impacts between poor, middle income, and rich; as well as net food-buying and net food-selling households. A key feature of agricultural households

in many developing countries is that their production decisions may not be separable from their consumption decisions due to market imperfections (Singh, et al., 1986). The issue of separability of household decision making needs to be settled first as a starting point and guidance for further in-depth analysis. When the household decision making is separable, one can solve the production and consumption sides of the model separately. First, on the production side, one seeks to maximize the net agricultural profits of the households under risky weather conditions, and then in the second stage, based on this maximized production one maximizes household's utility from consumption. The consumption decisions do not influence the production decisions. Households consider goods produced at home or outside as perfect substitutes. Similarly, family labor and hired labor are also considered as perfect substitutes. In the alternative case, when household decision making is non-separable, consumption side influences the production. For example, family characteristics and demographics may have significant effects on the household's choice of production technology, use of inputs and ultimately, production outcomes. The choice of the model to apply would be crucial for the final estimation results in terms of agricultural production values, consumption levels and poverty rates, as well as supply of family labor to different economic activities.

No matter whether decision-making is separable or non-separable, agricultural households' food consumption and poverty levels are affected by weather shocks through their impact on agricultural households' farming profits. Structurally, this could be through the effects of weather shocks on crop yields and/or crop prices. Hence to see the potential impact of weather shocks on households' food security, the income and price elasticities of households' food expenditures need to be identified. The major objective of this analysis is to evaluate how these income and price changes may translate in terms of households' access to food. Moreover, as discussed in the introduction, I also seek to differentiate these impacts by different household categories.

Risk attitudes of agricultural households may play an important role in their decision-making and economic performances. Risk-averseness may lead to sub-optimal economic outcomes for agricultural households. Therefore, poverty reduction may necessitate the use of methods to better manage such risks, for example through agricultural insurance (Ito & Kurosaki, 2009), or other forms of collective action. Weather risks are usually covariate, while adaptive capacities, resilience and market failures are idiosyncratic. In contrast to idiosyncratic risks, agricultural households find it much more difficult to insure against covariate risks (Rosenzweig & Binswanger, 1993). Difficulty to insure against weather risks leads

agricultural households to factor in potential weather risks in their production decisions in an ex ante manner (ibid.). Incorporation of risk attitudes of households in the models estimated in this study is constrained by lack of adequate data, requiring more research in the future for explicitly accounting for households' risk attitudes.

4. Empirical Strategy

In econometric terms, the difference between separable and non-separable models is that in the non-separable model farming profits are endogenous with consumption. To address this issue of endogeneity, econometric estimation of non-separable model requires the use of instrumental variables that would be highly correlated with farming profits and not endogenous with the consumption. The instrumental variables should affect consumption only through their effect on production. Climate variables or specifically, long-term temperature and precipitation variability, can be obvious candidates for the role of instrumental variables in such a setting. Temperature and rainfall variability have important effects on agricultural profitability by influencing many aspects of agricultural production such as the choice of crop cultivars, planting dates, soil moisture content, etc, however, clearly local weather variability is not caused by current levels of consumption of households residing in that locality. Moreover, the use of climate variables as instruments in this context enables to link these climate variables to household livelihoods through their effect on agricultural incomes. Naturally, the validity of these suggested instruments is evaluated using various identification tests.

The empirical estimation involves four steps. The first step is to test for separability of the agricultural household model. Taking into account the recommendations from Vakis et al. (2004) about the importance of accounting for heterogeneous household behavior in testing for separability, giving preference to using a reduced form approach, and making sure that the estimation method is able to identify unknown sample separation for obtaining results on households' behavior which are not confined to one specific market, finite mixture regression is employed to identify latent idiosyncratic non-separability among heterogeneous households (Table 2). Finite mixture regression uses maximum likelihood estimation for identifying sub-populations within an overall population (McLachlan & Peel, 2000). Finite mixture models (FMM) are especially useful for modeling unknown distributional shapes. While estimating FMM, one can give the number of latent components in the data within

which observations behave differently. For example, within the agricultural household model framework, household behavior is classified into separable and non-separable, i.e. two components. However, one may not know which households behave in separable manner and which in non-separable manner. Using the results from the FMM regression, the households can be classified into these two categories: for example, those households whose family labor allocation to own on-farm agricultural production is influenced by their demographic characteristics in a statistically significant manner are thought to behave in non-separable manner, and vice versa.

Second, assuming non-separability, a two-stage model is run: in the first stage the endogenous variable (farming profits) is regressed on the suggested instrumental variables (temperature and rainfall variability), from which the predicted values for the farming profits are obtained. Then, the latter are plugged into the second stage regression, where I employ quantile regression of consumption expenditures per household member on a number of explanatory variables including the now instrumented farming profits, household characteristics, asset ownership, crop prices, and several institutional and community variables such as market access, etc. The reason for using quantile regression is to see the effect of these variables on different household categories, especially the poorest ones. When relationship and interactions between the right- and left-hand side variables are complex and can vary at different ranges of data distribution, the Ordinary Least Squares (OLS) estimation may miss the important differences on how different quantiles of the dependent variable react to the same explanatory variables (Cade & Noon, 2003). In the present case, using OLS or other similar methods based on estimating the relationship between the variables at the means of these variables would completely miss whether poor or rich households in the sample are affected differently by the same external factors. Another advantage of quantile regression is that it is more robust to outliers than OLS.

In the third stage, separability is alternatively assumed and quantile regression of consumption is run without instrumenting for endogeneity between consumption and farming profits as above, but by using observed values of farming profits.

Finally, instrumented and non-instrumented versions of the quantile regressions are run following the results of separability test: instrumented version for households with non-separable behavior and not instrumented version for households with separable behavior.

5. Data

The data used in the analysis comes from the nationally representative agricultural household surveys conducted in the countries of Central Asia during 20101. The multi-stage survey sampling was conducted in a way to ensure representativeness of the survey sample with the overall population of agricultural producers: farmers, household producers, and cooperatives (where they exist) across different agro-ecologies and farming systems in each country. The confidence interval of 95% was used to calculate the sample size. The sample size varied between 380 and 385 respondents between the countries. To compensate for any missing or failed cases, the sample size for each country was determined to be 400 respondents, i.e. 1600 respondents in total. Uzbekistan and Kazakhstan (bigger countries) were first divided into major agro-ecological zones – west, south, center and east for Uzbekistan, north, center, west, south and east for Kazakhstan. Then in each zone, one province was randomly selected. In the case of Tajikistan and Kyrgyzstan (smaller countries) all provinces were selected for further sampling of villages in each of them. The number of respondents was allocated to each province depending on the share of the agro-ecological zone (or province, in the cases of Tajikistan and Kyrgyzstan) in the value of the national agricultural production. Following this, the total list of villages was obtained for each province selected. The villages in each province were numbered, and the corresponding numbers for the selected villages were randomly drawn using the appropriate Excel software function (35 villages in Kazakhstan, 22 in Kyrgyzstan, 25 in Tajikistan, 25 in Uzbekistan). The number of respondents per village was evenly distributed within each province. At the village level, the list of all agricultural producers, including household producers, were obtained from the local administrations; agricultural producers were numbered, and then from this numbered list, respondents were randomly selected. Due to civil unrest during most of 2010 in southern Kyrgyzstan, it was impossible to include the three provinces in the south of Kyrgyzstan in the sampling. Similarly, Gorno-Badahshan autonomous province of Tajikistan was also excluded from sampling due its trivial share in agricultural production and population, as well as extremely high surveying costs due to its location in high altitude areas with difficult access.

The regression models include such standard household variables as family size, age, gender and education of the household head. It is expected that higher family size is associated with lower per head food consumption levels. The value of the livestock by the household can be a

[1] The survey was conducted by the International Center for Agricultural Research in the Dry Areas (ICARDA) under the project funded by the Asian Development Bank (ADB). The author is grateful to ICARDA for allowing access to the survey dataset, and to ADB for funding this highly useful survey.

good indicator of the level of climate change adaptive capacities and income smoothing options after weather shocks. Total farm size is expected to have a positive effect on consumption levels as economies of scale could allow increasing per hectare farming profits and also enable the use of more productive agricultural machinery. Number of crops grown (diversity of crop portfolio), could positively influence consumption levels. Land tenure is a potentially important factor influencing farmers´ decisions. Farmers in Central Asia may operate several parcels with different tenure arrangements ranging from privately owned to those leased from the State. To instrumentalize this in one variable, the share of privately owned land area in the total farm size is calculated. Better market access could lead to improved opportunities for commercializing agricultural produce thus creating favorable conditions for higher farm earnings. The model seeks to capture the effects of better market access by interpolating the distance to nearest urban markets for each household in the sample from the global dataset by Nelson (2008).

In addition to these variables, several new variables are introduced which are expected to have a strong explanatory power in the estimated models. One of these variables is called as rural development, standing for the dynamism and institutional power of the rural areas, which can serve as a good proxy variable standing for availability of non-farm employment opportunities in the area. This variable is an interaction of the Nelson (2008) data on distance to major urban centers and intensity of night-time lighting2. A binomial variable was created for classifying households into net sellers and net buyers of agricultural commodities, chiefly food. This variable was created by subtracting the amount of money spent on food expenses from total agricultural sales. All households which sold more than bought were classified as net sellers, and vice versa. If farmers were growing crops but not selling them, they were classified as subsistence farmers, and non-subsistence farmers if they were selling any of their agricultural produce. Cooperation can be an important element of collective action for managing various risks and adapting to climate change. Farmers' mutual knowledge exchange and ability to learn from their peers can be a good proxy indicator for their willingness for collective action. The ratio of the number of SLM technologies farmers learned from other farmers divided by the number of all other SLM technologies they learned from all other sources is used to instrumentalize for farmers potential for collective action. In

[2] DMSP-OLS Nighttime Lights Time Series. NOAA's National Geophysical Data Center. Data collected by US Air Force Weather Agency. http://www.ngdc.noaa.gov/dmsp/downloadV4composites.html

fact, (Ringler, Bryan, Hassan, Alemu, & Hillesland, 2008) find that farmer-to-farmer extension increases the probability of adaptation to climate change. Within a cross-sectional setting, it is hypothesized that spatial variation of prices within a given area, such as a province: ratio between minimum and maximum prices in the province at a given time can also be indicative of the extent of market integration. Strong spatial variation is consequent to the existence of market failures or of isolated and disintegrated markets, which are more sensitive to local weather shocks, thus making them more vulnerable to inter-temporal price variations as well. Thus, high spatial variation in prices is indicative of market fragmentation and high transportation costs. So in the regression analysis this new variable is as a proxy for market integration. The country dummies are included to implicitly account for other country-specific characteristics that are not included in the models explicitly. In addition, the prices for several key staple crops in the region are used to estimate price elasticities of consumption depending on different household categories.

6. Results and Discussion

Before going to the results of our econometric analysis, some descriptive statistics of several important variables are presented in order to provide an overview of the sampled households (Table 1). In most key parameters, characteristics of households across the four countries of Central Asia are quite similar. Notable exception is the average farm size in which average farm sizes in Uzbekistan and especially in Kazakhstan are much bigger than in Tajikistan and Kyrgyzstan. In Kazakhstan and Tajikistan, higher share of agricultural households are headed by females than in Uzbekistan and Kyrgyzstan. Per capita expenses for food and other consumption items in Kazakhstan sample are considerably higher than in the rest of the region.

The separability tests were conducted for both labor and goods markets using finite mixture model regression (Tables 2-3). While testing for separability using the household labor supply, the family size and dependency ratio were found to significantly influence the on-farm family labor supply for the households in the first category (n=415), while for those households in the second category (n=1125) none of the demographic characteristics were significant determinants of on-farm family labor supply. Those households for which household demographics are not significant in determining family labor force allocation can be classified as making decision in a separable manner, while those for whom household

characteristics are significant determinants of labor supply can be thought to behave in non-separable manner. The results point out that the decision making among our households using this criterion is separable for households in Component 2, and non-separable for those in Component 1 (Table 2). Similarly, another separability test was conducted using the value of net agricultural trade balance, i.e. the difference between the value of agricultural goods sold and bought by the households. If the household behaves in separable manner, the household's demographic characteristics should not influence its net agricultural trade balance in a statistically significant way, since household would consider goods produced at home or outside as perfect substitutes.

<include Table 1 here>

<include Table 2 here>

By this measure, 437 households (Component 1) in were found to behave in non-separable manner and 1095 households (Component 2) in separable manner (Table 3).

<include Table 3 here>

The Pearson chi2 test rejected at 1% that the results of the two separability tests are independent from each other (Table 4), i.e. meaning that both tests mostly agreed, and in most cases the same households were found to behave in non-separable manner by both tests, and vice versa. At the same time, the tests showed that there are some households who may be behave in separable manner in the labor market, but behave in non-separable way in the goods market, and vice versa.

<include Table 4 here>

Before estimating the non-separable model, the validity of the instruments was checked using various identification tests. When both variation in temperature and precipitation were used, the model was over-identified with Hansen J-Statistic equal to 3.39 (p-value = 0.0653), when only variation in precipitation was used the model was under-identified with Kleibergen-Paap LM statistic equal to 1.094 (Chi-sq(1) P-val = 0.2956), whereas when only variation in temperature was used the model was exactly identified. In the latter case, the null hypothesis

of under-identification was rejected at 1% both for i.i.d. and non-i.i.d. assumptions for error terms with corresponding LM statistic of Anderson canonical correlation and Kleibergen-Paap LM Statistic. The Sargan-Hansen test indicated that the model is exactly identified. The model was calculated also without instrumenting for farming profits (separable model), and then compared to the above instrumented version (non-separable model) using Hausman specification test resulting at rejection of the null hypothesis of no systematic difference in the coefficients at 1%.

The results of non-separable and separable model estimation are given in Tables 5 and 4, respectively. These two models assume that all household behave either in separable or non-separable manner. The major difference between separable and non-separable models is in the income3 elasticity of food consumption and income coefficients depending on the population quantiles: in the non-separable model 1% change in production income would translate into about 0.39%-0.52% change in consumption. The income elasticity of the poorest households (10th percentile) is higher than that of richer households (Table 5). In the separable model, the elasticities are significantly lower, less than 5% and mostly non-significant (Table 6).

However, in practice, some households in the sample may behave in separable manner, while at the same time; the remaining households behave in non-separable way. Using the results of separability tests, households were divided into two groups: those with separable behavior and those with non-separable behavior, using the separation given by the separability test of the labor market behavior. Quantile regressions of per capita household food expenditures were run separately for each of these two groups. When estimated separately, the model for households with non-separable behavior confirms the results of the general non-separable model. The results of the separable model for only those households which were found to have separable behavior are broadly similar with the general separable model (Annex 1).

Since income from agricultural activities is the most important explanatory variable in the analysis, based on the above results one can draw some conclusions on the relative strengths of each of these models. It appears that non-separable models better explain households' behavior, especially for the poorer households, since the income elasticities of food consumption in the separable models are implausibly low, especially considering that for most households in the sample agricultural income is the most important source of livelihoods. Moreover, as the separability tests have demonstrated, some households who

[3] Net income received from agricultural production.

seem to behave in a separable manner in one market may show non-separable behavior in some other market. For these reasons, while interpreting the results, the preference is given to the non-separable models.

The general non-separable model indicates that the poorest households' food consumption is quite sensitive to agricultural income changes: 1% increase in the level of their farming profits may lead to about 0.52% increase in their per capita food consumption. For richer households, income from agricultural activities seems to have lower impact on their food consumption, about 0.39% increase for every 1% increase in farming profits (Figure 1).

The effects of the age, education and gender of household head are generally statistically non-significant at 5%. More households members working on-farm or non-farm seems to have statistically more significant effects, with more households members engaged in on-farm work decreasing per capita household food consumption, while more household members working in non-farm jobs leading to higher food consumption.

<include Table 5 here>

<include Table 6 here>

<include Figure 1 here>

Distance to markets is negatively associated with households' food consumption. Halving the time necessary to reach the nearest major urban market may likely increase the households' food consumption by about 5-10%. A separate analysis shows that this is probably because both of the possibility to get higher prices for agricultural produce in the urban markets, but also, importantly, the higher chances of having a family member working in a non-farm job in the city. As expected, the value of livestock owned is mostly positively associated with food consumption; however, the coefficients are statistically non-significant. Whereas the value of total assets owned has a clear positive association with higher food consumption across all household categories. The instrumental variable on market integration is negatively associated with food expenses in all models, i.e. higher market integration seems to be associated with lower expenditures on food. The instrumental variable on cooperation does not seem to be a good one, as it was non-significant in most cases, even though positively signed. Being a net seller of agricultural commodities (including non-food, such as cotton) seems negatively associated with food expenditures. Being a non-subsistence farmer, i.e.

commercializing at least some part of household's agricultural output and growing a more diversified crop portfolio both seem to lead to higher food consumption.

In all cases when vegetable, wheat and maize prices are statistically significant; they are negatively associated with food expenditures, which is consistent with classical demand theory. However, in most cases, potato prices are positively associated with food expenses, especially for the poorer households, pointing at the importance of potato in the agricultural production by poor households and as a source of their income.

The share of privately owned land was negatively associated with food expenses, perhaps pointing that those farmers who are able to rent more land then they own privately would have higher profits and thus higher food consumption. Confirming this idea, total farm size was positively associated with food consumption for the richest households. In all models, the country dummies are included to account for unobserved country-specific characteristics, and also all the models have been village-clustered and bootstrapped with 20 replications for achieving robust standard errors. These results are presented graphically in Figure 2.

<include Figure 2 here>

7. Conclusions

The study has confirmed that poorer households are more vulnerable to the impacts of weather and climate shocks since their food security more strongly depends on their agricultural incomes. The agricultural income elasticities of the poorest 10% of households in our sample is estimated to be about 0.52, meaning every 1% decrease in their farming profits is likely to lead to 0.52% decrease in their food expenses. Improving market access and creating opportunities for diversified crop portfolio seem to positively contribute to improving food security among the rural farming households in Central Asia.

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Table 1. Household descriptive statistics

Key indicators	**Kazakhstan**	**Kyrgyzstan**	**Tajikistan**	**Uzbekistan**
Average family size	5.7	5.5	7.8	6.2
Females to males ratio	1.18	1.13	1.04	1.06
Share of female household heads	21%	8%	15%	6%
Age of household head	51	50	52	47
Dependancy ratio	0.69	0.67	0.68	0.78
Family labor allocation, (%)				
off-farm work	26%	20%	23%	24%
employment abroad	0%	4%	4%	1%
farm work	73%	76%	73%	75%
Food expenditures, daily per cap (current USD)	1.72	0.80	0.71	0.93
Non-food expenditures, daily per cap (cur. USD)	1.07	0.39	0.30	0.56
Share of food expenditures in total expenses (%)	60%	67%	66%	62%
Average farm size, (ha)	191	5	3	26
Average house value, (USD)	13044	5682	5836	14075
Average value of agricultural machinery owned, (USD)	25084	2287	514	10164
Average value of livestock owned, (USD)	5251	8973	852	6507

Table 2. Separability test based on family labor supply to household own farm

Variables	**Component 1**	**Component 2**
Dependency ratio	-0.37**	-0.10
Female to male ratio	-0.02	0.09
Household head age	-0.06	0.04
Household head age, squared	0.00	-0.0003
Household head gender	-0.18	0.06
Family size	-0.15**	-0.07
Number of adults	0.16	0.03
Education of household head	-0.01	0.01
Average wage	0.96***	-0.001
Distance to markets	0.0	-0.001*
Rural development	0.0004***	0.00001
Country dummies	0.90	-0.01
Farm size	0.0002**	-0.00001
Number of crops grown	1.54***	0.79***
Constant	-4.26	-0.92

Dependent variable: Supply of family labor to own on-farm activities

*** p<0.01, ** p<0.05, * p<0.1

Table 3. Separability test based on household's net trade balance in agricultural goods

Variables	**Component 1**	**Component 2**
Dependency ratio	-0.0495	-0.01991
Female to male ratio	0.013439	-0.00287
Household head age	-0.00955	0.005218
Household head age, squared	1.82E-06	-5.2E-05
Household head gender	0.043274	0.027667
Family size	-0.46939**	-0.03816
Number of adults	0.059797	-0.00939
Education of household head	0.112691***	0.000917
Average wage	0.15069	-0.20578***
Distance to markets	0.000118	-2.8E-05
Rural development	0.00012*	1.45E-05*
Country dummies	0.376508***	-0.04612***
Farm size	-1.43E-06	0.000364***
Number of crops grown	0.239087***	0.035535***
Constant	8.289252***	9.827911***

Dependent variable: Net balance in agricultural goods trade (in log) *** p<0.01, ** p<0.05, * p<0.1

Table 4. Comparison of separability tests in labor and goods markets

	Goods market		
Labor market	non-separable	separable	Total
non-separable	147	268	415
separable	290	827	1117
Total	437	1095	1532

Pearson chi2(1) = 13.2795 Pr = 0.000

Table 5. Model estimation with instrumental variable assuming non-separability

Variables	Quantiles				
	10th	**30th**	**50th**	**70th**	**90th**
Farming profits (log, instrumented)	0.522***	0.494***	0.437***	0.378**	0.392**
Age of household head	0.0132	0.0105	-0.0122	-0.0185*	-0.0268
Age of household head, squared	-0.00016	-0.00015	0.000109	0.000176*	0.000271
Education of household head	0.00106	-0.108	-0.152**	-0.161**	-0.0503
Education of household head, squared	0.000218	0.0225	0.0345**	0.0355***	0.00862
Gender of household head					
(0-female, 1-male)	0.0846	-0.0427	-0.0508	-0.0456	-0.0842
Number of family members working:					
Non-farm work	0.0369	0.0371*	0.0525***	0.0590**	0.0457
On-farm work	-0.0417**	-0.0471***	-0.0557***	-0.0569***	-0.0551***
Distance to markets (log)	-0.0779**	-0.0929***	-0.0552***	-0.0426*	-0.0721**
Livestock value (USD)	5.99E-07	3.59E-07	2.44E-07	3.65E-08	1.95E-06
Value of total assets (log)	0.0632**	0.0735***	0.0567***	0.0392***	0.0468**
Market integration	-0.550***	-0.316***	-0.342***	-0.252*	-0.422***
Cooperation	0.00569	0.00843	0.0224	0.0338	0.0357
Net agricultural trade position					
(0-net buyer, 1-net seller)	-0.284***	-0.219***	-0.187***	-0.178***	-0.157*
Number of crops grown	0.0575**	0.0487***	0.0332	0.0222	0.00637
Subsistence farmer (0-yes, 1-no)	0.355***	0.409***	0.408***	0.348**	0.188
Vegetable price (log)	-0.0483*	-0.0223	-0.0153	-0.0088	-0.0102
Potato price (log)	0.395***	0.492***	0.310*	0.261*	0.217
Wheat price (log)	-0.0669	-0.0726	-0.196	-0.255	-0.165
Maize price (log)	-0.185***	-0.147***	-0.0865**	-0.0438	0.0298
Country dummies	-0.228***	-0.236***	-0.245***	-0.226***	-0.229***
Share of privately owned land	-0.218***	-0.175**	-0.134*	-0.0507	0.0783
Farm size (log)	-0.00192	-0.0165	-0.00925	0.0129	0.0382**
Constant	-4.042***	-3.141***	-2.292**	-1.549	-0.675
Pseudo R2	18%	20%	21%	20%	19%

Notes: Dependent variable: Food consumption expenses per household member, log. Instrumental variable: Long-term variation in temperature. Bootstrapped 20 times.

*** p<0.01, ** p<0.05, * .1

Table 6. Model estimation without instrumental variable assuming separability

Variables	Quantiles				
	10th	**30th**	**50th**	**70th**	**90th**
Farming profits (log)	0.0345	0.0370*	0.0427***	0.0443***	0.027
Age of household head	0.00892	0.00281	-0.00342	-0.0172***	-0.0101
Age of household head, squared	-0.00015	-6.91E-05	3.36E-05	0.000157***	0.000111
Education of household head	0.0982	-0.108	-0.136*	-0.116*	0.00848
Education of household head, squared	-0.0196	0.0253	0.0345**	0.0262*	-0.00031
Gender of household head					
(0-female, 1-male)	-0.0182	-0.0584	-0.0366	0.00104	-0.0258
Number of family members working:					
Non-farm work	-0.0229	0.0688**	0.0582**	0.0577**	0.0249
On-farm work	0.000288	-0.0529***	-0.0558***	-0.0565***	-0.0467**
Distance to markets (log)	-0.0382	-0.0826***	-0.0428	-0.00682	-0.0103
Livestock value (USD)	4.43E-07	2.58E-07	1.24E-07	-1.31E-07	-4.79E-07
Value of total assets (log)	0.0546***	0.0569***	0.0332	0.0320**	0.0337*
Market integration	-0.614***	-0.387***	-0.430***	-0.455***	-0.729***
Cooperation	0.00764	0.0328**	0.0274	0.0347**	0.0531*
Net agricultural trade position					
(0-net buyer, 1-net seller)	-0.326***	-0.341***	-0.267***	-0.239***	-0.188**
Number of crops grown	0.0746***	0.0342*	0.0171	0.0105	0.0226
Subsistence farmer (0-yes, 1-no)	0.380*	0.496**	0.391*	0.4	0.214
Vegetable price (log)	-0.0487	-0.0116	-0.0209	-0.0225	-0.00573
Potato price (log)	0.473*	0.496***	0.511***	0.293*	-0.0326
Wheat price (log)	-0.432	-0.298	-0.374**	-0.311*	-0.287
Maize price (log)	-0.123	-0.130**	-0.122**	-0.0921	-0.0507
Country dummies	-0.230***	-0.224***	-0.236***	-0.245***	-0.314***
Share of privately owned land	-0.405***	-0.273***	-0.227***	-0.146**	0.0182
Farm size (log)	-0.015	0.0109	0.00709	0.0223	0.0563***
Constant	-0.964	0.0925	0.473	0.75	1.005**
Pseudo R2	18%	18%	20%	20%	18%

Notes: Dependent variable: Food consumption expenses per household member, log. Bootstrapped 20 times. *** p<0.01, ** p<0.05, * .1

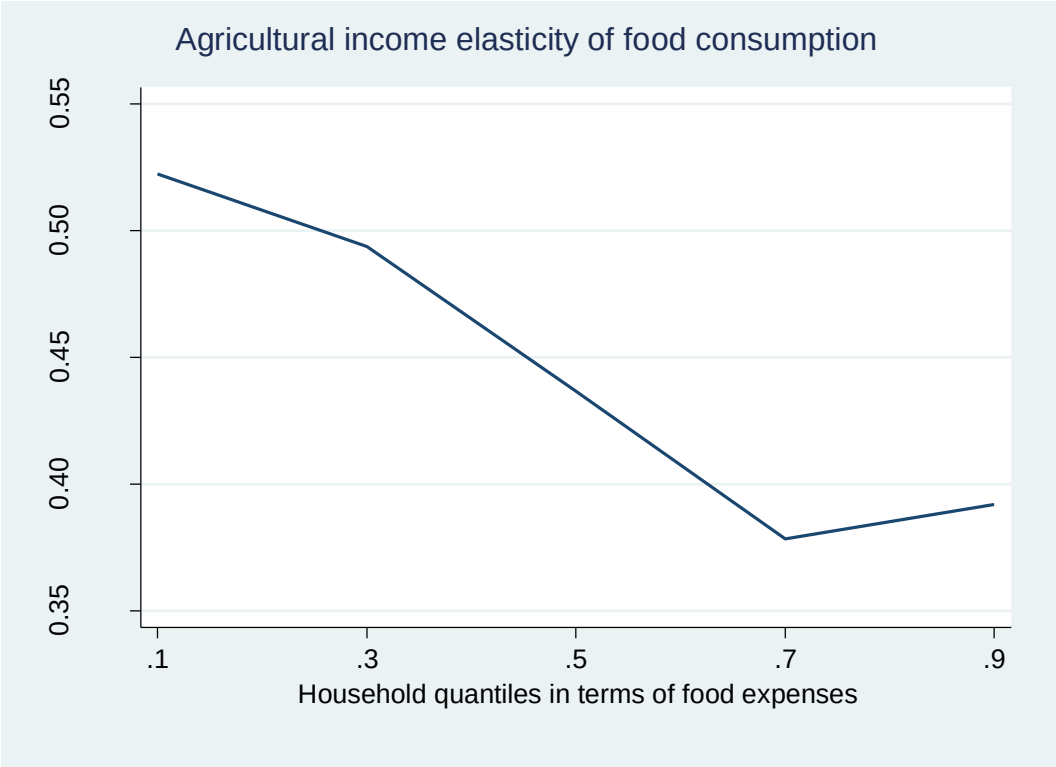

Figure 1. Impact of agricultural income on household food consumption (non-separable model).

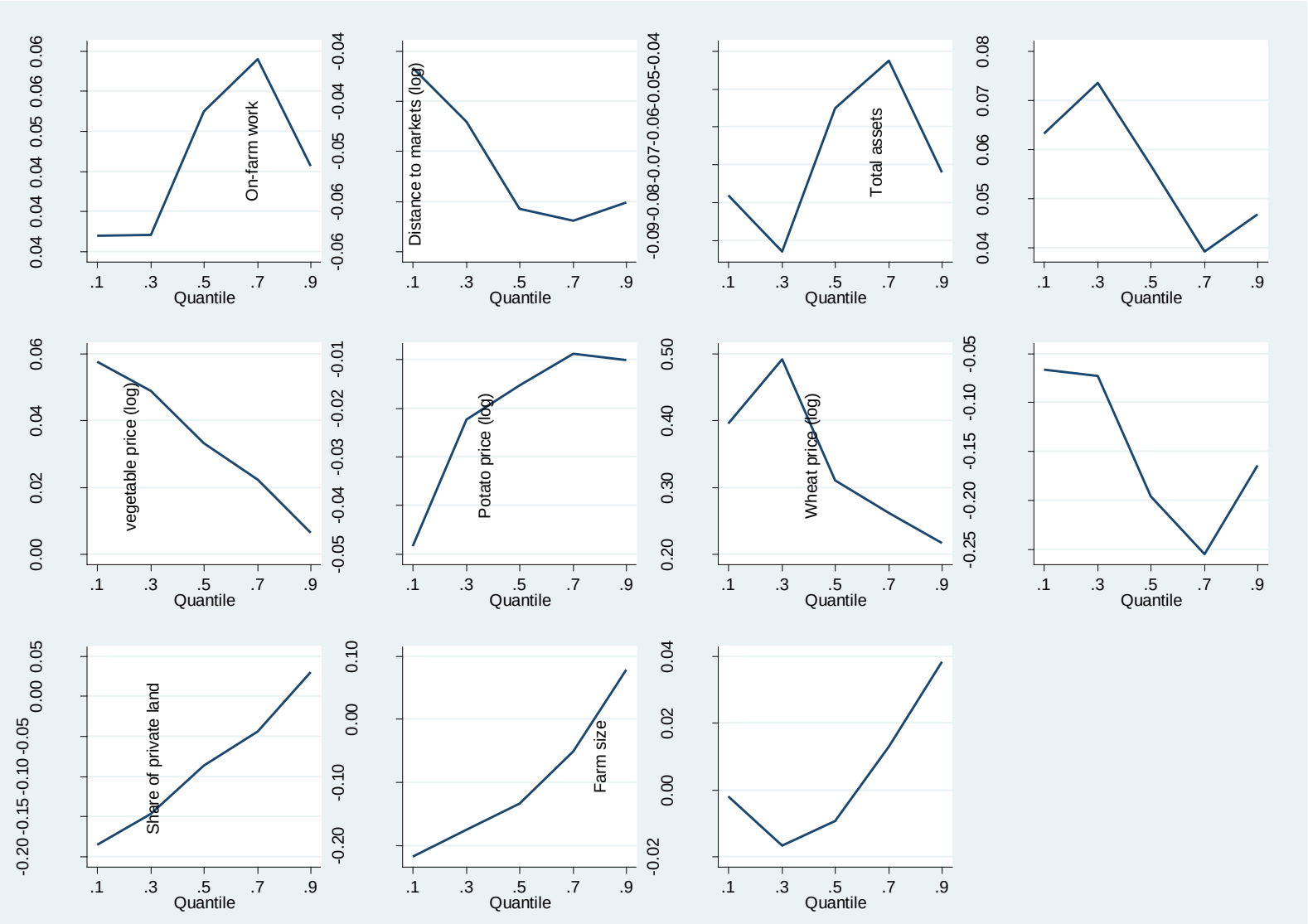

Figure 2. The results of general non-separable model.

Annex 1. Alternative model estimates

Table A1.1. Model estimation with instrumental variable only for households with non-separable decision making

Variables	Quantiles				
	10th	30th	50th	70th	90th
Farming profits (log, instrumented)	0.306	0.421**	0.396*	0.502*	0.211
Age of household head	0.022	0.0365**	0.0242	0.00772	0.000419
Age of household head, squared	-0.00022	-0.000373**	-0.00026	-4.59E-05	3.86E-05
Education of household head	0.151	0.0169	-0.274	0.0471	-0.00431
Education of household head, squared	-0.0294	-0.00477	0.0600*	0.00583	0.00953
Gender of household head					
(0-female, 1-male)	-0.00329	-0.115	-0.0459	0.011	0.0917
Number of family members working:					
Non-farm work	0.05	0.0113	0.0281	0.0790**	-0.0283
On-farm work	-0.0363	-0.0254	-0.0425	-0.0871***	-0.0429
Distance to markets (log)	-0.0188	-0.0937**	-0.043	-0.0579	-0.0783
Livestock value (USD)	4.29E-06	4.77E-07	-2.13E-06	-1.66E-06	-4.66E-06
Value of total assets (log)	0.0868	0.0621**	0.0731**	0.0498	0.0726**
Market integration	0.151	0.0281	-0.0611	-0.312	-0.791**
Cooperation	0.00551	0.00249	0.0221	0.0184	0.0266
Net agricultural trade position					
(0-net buyer, 1-net seller)	-0.122	-0.0729	-0.0967	-0.190*	-0.212
Number of crops grown	0.0351	0.0203	-0.0205	-0.0257	0.0232
Subsistence farmer (0-yes, 1-no)	0.382	0.177	0.251	0.436	-0.00986
Vegetable price (log)	-0.0815	-0.0673	-0.0741	-0.0224	-0.00931
Potato price (log)	0.563	0.412	0.564*	0.298	-0.602
Wheat price (log)	-0.0499	-0.204	-0.144	0.04	-0.49
Maize price (log)	-0.247**	-0.198**	-0.141**	-0.193***	-0.0885
Country dummies	0.02	-0.0842	-0.052	-0.198***	-0.352***
Share of privately owned land	-0.464**	-0.116	-0.00058	-0.0374	-0.0374
Farm size (log)	-0.0373	0.00812	0.0184	0.0527*	0.0345
Constant	-4.375**	-4.322**	-3.358**	-3.031	-1.421
Pseudo R2	18%	18%	17%	18%	20%

Table A1.2. Model estimation without instrumental variable only for households with separable decision making

Variables	**Quantiles**				
	10th	**30th**	**50th**	**70th**	**90th**
Farming profits (log)	0.0619*	0.0482**	0.0539**	0.0548**	0.0863**
Age of household head	0.0185	0.00106	-0.0202	-0.0194	-0.0173
Age of household head, squared	-0.00025	-4.33E-05	0.000189	0.000167	0.000171
Education of household head	0.191	-0.0614	-0.11	-0.0913	0.0533
Education of household head, squared	-0.0392	0.0139	0.0231	0.0185	-0.0133
Gender of household head					
(0-female, 1-male)	0.0106	0.0663	0.0237	-0.0147	-0.181
Non-farm work	-0.00657	0.106***	0.0851**	0.0585	0.0682**
On-farm work	-0.00274	-0.0687***	-0.0640**	-0.0512**	-0.0645***
Distance to markets (log)	-0.078	-0.112***	-0.0521*	-0.0211	-0.0111
Livestock value (USD)	5.75E-07	2.02E-07	4.06E-08	-5.33E-08	-3.18E-07
Value of total assets (log)	0.0492***	0.0397*	0.0396*	0.0435*	0.00305
Market integration	-0.609**	-0.530***	-0.534***	-0.541***	-0.560***
Cooperation	0.0508	0.0468*	0.0521*	0.0456	0.0934**
Net agricultural trade position					
(0-net buyer, 1-net seller)	-0.477***	-0.415***	-0.330***	-0.267***	-0.229***
Number of crops grown	0.107***	0.0362	0.0382	0.0223	0.0342
Subsistence farmer (0-yes, 1-no)	0.289	0.152	0.411*	0.35	0.161
Vegetable price (log)	-0.0638	-0.00552	-0.0372	-0.0345	-0.0145
Potato price (log)	0.425	0.494**	0.415*	0.146	0.0787
Wheat price (log)	-0.277	-0.314	-0.327	-0.234	-0.232
Maize price (log)	-0.206	-0.203***	-0.138**	-0.0962	-0.0713
Country dummies	-0.310***	-0.244***	-0.258***	-0.276***	-0.329***
Share of privately owned land	-0.290***	-0.242***	-0.186*	-0.0931	-0.0258
Farm size (log)	0.00816	0.023	0.0182	0.0137	0.0466**
Constant	-1.003	0.607	0.725	0.729	1.377**
Pseudo R2	21%	22%	22%	22%	22%