Part V

The Micro-Economics of Price Risk, Volatility and Price Shocks: Households, Firms and Communities

20 Access to Information and Price Expectation Errors of Smallholder Farmers: Theory and Empirics

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20.1 Introduction

Producers use different information when making decisions concerning their economic activities. Past trends, outcomes in related markets, media reports, weather, and published forecasts are some of the information that farmers use in their resource allocation decisions (Just and Rausser 1981). The intrinsic feature of agriculture—the lag between production decision and output realization—makes these types of information indispensable to agricultural producers. Besides, agricultural production is inherently stochastic due to weather shocks, pest infestations, and other shocks, which affect the general market supply condition and therefore prices. Farmers need to form their expectations of market prices and potential yield for the upcoming harvesting season in order to make their production decisions. They invest in accessing and processing price and other market information, which they believe affects prices at harvesting time. This study assesses the information sources relevant to smallholder farmers and how efficiently farmers utilize the available information in their price expectation formations. This is important since modeling price expectations is an integral part of any agricultural supply response study (Moschini and Hennessy 2001).

In this study, we seek to empirically test the impact of access to information on the level of investment in information acquisition. Access to information is used synonymously with low costs of acquiring information to forecast future prices, which is notably a continuous rather than a discrete concept. Whereas ownership of information and communications technologies (ICT) and distance to markets serve as a measure of access to information (or costs of acquiring information), we use farmer realized price forecasting errors as a measure of the outcome

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M. Kalkuhl et al. (eds.), *Food Price Volatility and Its Implications for Food Security and Policy*, DOI 10.1007/978-3-319-28201-5_20

variable of interest. In particular, we seek to address the research question whether access to information (i.e., access to ICT and grain markets) results in a smaller price forecasting error of smallholder farmers in rural Ethiopia. Analyzing the distribution of smallholders' price expectations relative to realized prices assists policymakers in delivering information on price outlook and price risk management strategies. The main findings indicate that smallholders who have access to ICT and who reside closer to major grain markets are more likely to have smaller price forecasting errors. Public investment in both information and physical infrastructure that reduces the cost of accessing information is therefore vital for improving the precision of farmers' price expectations.

Several approaches have been applied to model expectations of agricultural producers. These include naïve expectation (Ezekiel 1938), whereby expected prices are assumed to be equal to the latest observed prices; adaptive expectation (Nerlove 1958), whereby farmers are assumed to revise their expectations depending on past errors; and rational expectation (Muth 1961), which assumes that expectations are consistent with the underlying market structure and that economic agents make efficient use of all available information. Other research has focused on modeling supply response using a quasi-rational price expectation (Holt and McKenzie 2003), which is consistent with price prediction from a reduced-form dynamic regression equation. Futures prices have also been used as proxies for price expectations (Gardner 1976).

Acquiring information is a common and critical feature of all of these expectation hypotheses. Because searching for and processing information are costly (Stigler 1961), it is unlikely that producers make use of all available information to form their price expectations (Orazem and Miranowski 1986). This is even more so in the context of subsistent smallholder farmers with limited access to credit and capital. Farmers therefore gather and process price and other market information that could potentially improve their price forecasts the most. A rational farmer invests in acquiring market information to the extent that the expected marginal benefit (in terms of more accurate price expectation) is greater or equal to the marginal cost of investing in acquiring the information. Ownership of information assets, such as a radio, a television, and a phone, and proximity to grain markets could potentially reduce the costs of investing in acquiring information. The government could also improve market efficiency by lowering the costs of access to information by providing market information as a public good through organized market information systems.

There is a large body of literature that investigates the effect of market information systems (MIS) or ICTs on the economic performances of farmers, traders, and consumers. Most of the existing empirical work has focused on the impact of MIS or ICTs on price dispersion between markets and sellers (Aker and Fafchamps 2015; Jensen 2007), price asymmetry between traders and farmers (Svensson and Yanagizawa 2009), traders' search behavior (Tack and Aker 2014), farmers bargaining power and selling prices (Mitchell 2011), consumption expenditures (Labonne and Chase 2009), and farmers' marketing choices (Tadesse and Bahiigwa 2015), among others (see Nakasone et al. 2014 for a recent review). The empirical evidence has been mixed regarding the effect of improved market price information on prices at micro level. Yet, there seems to be little evidence arguing against its positive effect on lowering price dispersion and search costs and improving agricultural market performance at a macro-scale (Nakasone et al. 2014). Access to better information through ownership of mobile phones, a radio, or a television could potentially assist farmers in making a more informed price expectation. This, in turn, helps them to make better decisions in terms of their crop choices, the amount to plant, land management efforts, and the amount and type of investment that they undertake in each cropping season. The present study therefore uses primary data from smallholders in Ethiopia to empirically evaluate the impact of access to information on farmers' price expectations.

The remainder of this chapter is organized as follows: The following section presents a theoretical model that studies the importance of market information in improving the price signal for farmers. Section 20.3 outlines the empirical model, the data, and some descriptive statistics. Section 20.4 presents and discusses the econometric results, and the last section concludes this chapter.

20.2 Theoretical Model

We employ a simple theoretical model to understand farmers' decision behaviors on production and information acquisition. The model consists of two stages: a production decision (second stage) and a decision about investment in information acquisition (first stage). The model is solved by backward induction. We therefore start with the second stage.

Consider a farmer who decides on the output level y given a quadratic production cost $c(y) = \alpha y^2$. Crop prices are assumed to be random with mean μ and variance σ^2. Because production costs accrue before harvesting, the farmer maximizes discounted revenue from crop sales. With a discount rate of r (cost of capital), the farmer maximizes expected profits:

$$\max_y E\left[\frac{py}{1+r} - c(y)\right] = \frac{E[p]\,y}{1+r} - c(y). \tag{20.1}$$

The first-order condition is $\frac{E[p]}{1+r} = c'(y) = 2\alpha y$. With rational expectations (i.e., $E[p] = \mu$) the optimal production under uncertainty is given by $y^* = \frac{\mu}{2\alpha(1+r)}$. Substituting y^* into the expected profit function yields:

$$E[\pi_{\mathrm{v}}] = \frac{\mu}{1+r}\left(1 - \frac{1}{2\alpha}\right) + \frac{\mu^2}{(1+r)^2}\frac{1}{4\alpha}, \tag{20.2}$$

where the subscript v on π_{v} denotes profits under volatile prices. In case of no ex-ante uncertainty about prices, $E[p] = p$, the optimal production is $y^* = \frac{p}{2\alpha(1+r)}$, and thus the expected profit π_c conditional on the fact that the farmer knows the random price ex-ante is

$$E\left[\pi_{\mathrm{c}}\right]=E\left[\frac{p}{1+r}\left(1-\frac{1}{2\alpha}\right)+\frac{p^2}{(1+r)^2}\frac{1}{4\alpha}\right]=\frac{\mu}{1+r}\left(1-\frac{1}{2\alpha}\right)+\frac{E\left[p^2\right]}{(1+r)^2}\frac{1}{4\alpha}. \tag{20.3}$$

With $E\left[p^2\right]=\sigma^2+\mu^2$, we obtain

$$E\left[\pi_{\mathrm{c}}\right]=E\left[\pi_{\mathrm{v}}\right]+\frac{\sigma^2}{(1+r)^2}\frac{1}{4\alpha}. \tag{20.4}$$

Thus, farmers with access to perfect information on the harvest price are expected to have on average higher profits than farmers with uncertainty. The discrepancy increases with the magnitude of the uncertainty (variance σ^2).

In the first stage, the farmer chooses their level of investment in information acquisition, which results in acquisition of a perfect price signal regarding harvesting prices with probability ρ or no signal with probability $1-\rho$. With the probability $1-\rho$, the price remains as uncertain as it would be without any investment in information acquisition (i.e., the farmer receives no signal regarding harvesting prices). The cost of investing in information acquisition is given by a twice differentiable function $\beta k(\rho)$, where $k(0)=0,\ k'>0, k''>0, k(1)=\infty$ and β is a scaling factor. Hence, ρ measures the quality of the signal or the level of investment to obtain a perfect signal. The information investment decision involves choosing a $\rho\in[0,1]$ such that the expected profit—which is a weighted sum of the expected profit with certainty $E[\pi_{\mathrm{c}}]$ and the expected profit with uncertainty $E[\pi_{\mathrm{v}}]$—is maximized after the costs of information acquisition are netted out, thus:

$$\max_{\rho\in[0,1]}\ \rho E\left[\pi_{\mathrm{c}}\right]+(1-\rho)E\left[\pi_{\mathrm{v}}\right]-\beta k(\rho). \tag{20.5}$$

Given the profit in the second stage, the farmer chooses the optimal level of investment in information ρ^* to maximize the expected profit in the first stage. After substituting the expected profit from the second stage into Eq. (20.5), the first-order condition is obtained as:

$$\frac{\sigma^2}{(1+r)^2}\frac{1}{4\alpha\beta}=k'\left(\rho^*\right). \tag{20.6}$$

Proposition 1 The optimal investment in information ρ^* increases in σ^2 and decreases in r, a and β. Thus, investment in information acquisition increases with price volatility, whereas it is negatively correlated with discount rates, costs of acquiring information, and production costs.

Proof Calculating the total derivative in each parameter gives: $\frac{d\rho^*}{d\sigma^2} = \frac{1}{(1+r)^2\, 4\alpha\beta\, k''(\rho^*)} > 0$, $\frac{d\rho^*}{d\alpha} = -\frac{\sigma^2}{(1+r)^2\, 4\alpha^2\beta\, k''(\rho^*)} < 0$, $\frac{d\rho^*}{d\beta} = -\frac{\sigma^2}{(1+r)^2\, 4\alpha\beta^2\, k''(\rho^*)} < 0$ and $\frac{d\rho^*}{dr} = -\frac{2\sigma^2}{(1+r)^3\, 4\alpha\beta\, k''(\rho^*)} < 0$.

The magnitude of the forecasting error V of the price expectation formation of the farmer can be measured by the expected squared deviations of the expected prices p^{e} from realized prices p^{r}; thus $V = E\left[(p^{\mathrm{r}} - p^{\mathrm{e}})^2\right]$. The farmer's expected price p^{e}, in turn, depends on the level of information acquisition ρ and is $p^{\mathrm{e}} = \rho p^{\mathrm{r}} + (1-\rho)\,\mu$. It is the weighted sum of the realized price (revealed at probability ρ) and the unconditional mean μ of the random distribution of the price. Substituting p^{e} into V, we obtain $V = E\left[((1-\rho)\,(p^{\mathrm{r}} - \mu))^2\right] = (1-\rho)^2 E\left[(p^{\mathrm{r}} - \mu)^2\right]$, where $E\left[(p^{\mathrm{r}} - \mu)^2\right] = \sigma^2$ is the (unconditional) variance of the price.

Corollary 1 The magnitude of a farmer's forecasting error V (measured as the squared deviation of the farmer's expected price conditional on the information acquired from the realized price) is $V = (1-\rho)^2\sigma^2$. It increases with σ^2 and decreases with ρ.

One particular implication of the corollary is that in case of no information acquisition, that is, $\rho = 0$, the forecasting error is just the unconditional variance of the price series. For full information acquisition, $\rho = 1$, the forecasting error will be zero. As V decreases with ρ, the impact of the structural parameters on the forecasting error in the optimum V^* has a sign opposite to that of the impact of these parameters on ρ^*. The exception is σ^2, which influences both the optimal ρ^* and V^* in opposite directions.[1]

This chapter employs empirical analyses to validate the theoretical model and to determine the sign and magnitude of the impacts of the structural parameters on the accuracy of price expectation formation. Because it is nearly impossible to observe investment in acquiring information per se, we explain the size of the price expectation error (or realized price forecasting error) with empirical data. The structural model parameters are linked to our empirical data as indicated in the last column of Table 20.1.

[1]Formally, $\frac{\partial V^*}{\partial \sigma^2} = (\rho^* - 1)\left[(\rho^* - 1) + \frac{\sigma^2}{2\alpha\beta(1+r)^2 k''(\cdot)}\right]$ after substituting $\frac{d\rho^*}{d\sigma^2}$ from *proposition 1* into the derivative of V with respect to σ^2. As can be easily verified, $\frac{\partial V^*}{\partial \sigma^2} > 0$ for sufficiently small values of σ^2 and $\frac{\partial V^*}{\partial \sigma^2} < 0$ for sufficiently large values of σ^2.

Table 20.1 Impact of structural parameters on the quality of the price signal

Parameter in the theoretical model	Impact in optimum		Related explanatory variables in empirical model
	On the quality of the signal ρ	On the forecasting error V	
Cost of information β	$\rho^* (\beta) < 0$	$V^* (\beta) > 0$	Ownership of ICT, years of schooling, distance to market, distance to extension agents' office
Discount rate r	$\rho^*(r) < 0$	$V^*(r) > 0$	Discount rate, years of schooling
Production costs α	$\rho^* (\alpha) < 0$	$V^* (\alpha) > 0$	Distance to market, distance to extension agents' office, family labor
Volatility σ^2	$\rho^* \left(\sigma^2\right) > 0$	$V^* \left(\sigma^2\right) \gtrless 0$	Crop price volatility, crop and/or village fixed effects

20.3 Methods

20.3.1 Data and Descriptive Statistics

Data for this study were obtained through a household survey. A random sample of 415 rural smallholders were selected from seven villages out of four different districts of Ethiopia, namely Kersa, Shashemene, Ada'a, and Debre Birhan Zuria.[2] Adele Keke is a kebele[3] selected from Kersa district and households in this village trade with the adjacent towns of Dire-Dawa, Harar, and Aweday. Smallholders in this kebele produce staple crops, typically corn and sorghum, and cash crops, like chat[4] and potato. We also interviewed households from four neighboring kebeles at the Debre Birhan Zuria district, which is 120 km northeast of Addis Ababa. The town of Debre Birhan is a nearby market for their grain production, which typically consists of barley, wheat, and horse beans, among others. Sirbana Godeti is a kebele that was selected in the Ada'a district and it is the major supplier of *teff* to the surrounding and Addis Ababa markets. Having relatively fertile soil, smallholders in this area also produce several leguminous crops and vegetables.

[2]The households in our sample were those selected for the widely used Ethiopian Rural Household Survey (EHRS), and detailed information on sampling techniques can be found from Dercon and Hoddinott (2004).

[3]A kebele is the smallest administrative unit in Ethiopia.

[4]Chat is a perennial cash crop and a mild stimulant that is commonly used in the southern and eastern parts of Ethiopia.

Finally, we interviewed households from Turfe Ketchema, which is located about 12 km northeast from the town of Shashemene, where most of their marketing are conducted. The main crops that the smallholders in this survey area produce include potatoes, corn, wheat, barley, and *teff*.

The survey was conducted in April and May 2013, which was immediately before or at the onset of planting for the main "*meher*" season of 2014. This helped us obtain good information on planting time prices. Furthermore, the dataset provided detailed information on household demographics, asset holdings, production and consumption, purchases and sales, seasonal prices, information sources, among others. Data on sowing time prices from the nearby grain markets were obtained from the central statistical agency (CSA) of Ethiopia. Grain prices for the then upcoming harvesting prices, which were not known at the time of our survey, are obtained from three different enumerators who travelled to the respective markets to collect price information.

Following the liberalization of markets in Ethiopia in the early 1990s, prices have not only served as an incentive for farmers to produce more, but they have also become less predictable. Consequently, recent food price volatility has posed additional challenges to farmers in their production decisions. Information regarding input and output price developments, weather conditions, and input availability are hence crucial for the farmer to make a better production decision. Based on the survey data, most of the smallholder households perceive prices as highly unpredictable. About 85 % of the households reported that output prices were likely to increase in the next one year, whereas the other 11 % indicated that prices would have declined. Although most of the farmers (87 %) reported that changes in output prices (in a year) were more likely to range from a decrease by half to an increase by twice of the amount they predicted, the remaining households reported that prices could be outside this range.

Farmers form their price expectations based on information that they have access to. We asked the respondents two similar but subtly different questions regarding their sources of price information. First, we wanted to know the major sources of information for the market prices of their crops. Second, we asked them a more specific question with regard to what information they observe to predict the harvesting time price of the crop they chose to cultivate. Figure 20.1 shows the major responses. There are three main sources of price information for rural households in Ethiopia. Most of the smallholder farmers (54 %) visited close-by markets to sell or buy products and thereby gather price information for the commodities they are interested in, whereas about 45 % of them got price information from their fellow farmers. About two-thirds of the households owned either a radio (57 %) or a mobile phone (66 %), or a television (8 %), and about a quarter of the rural households reported using these ICT tools as their sources of output price information. The

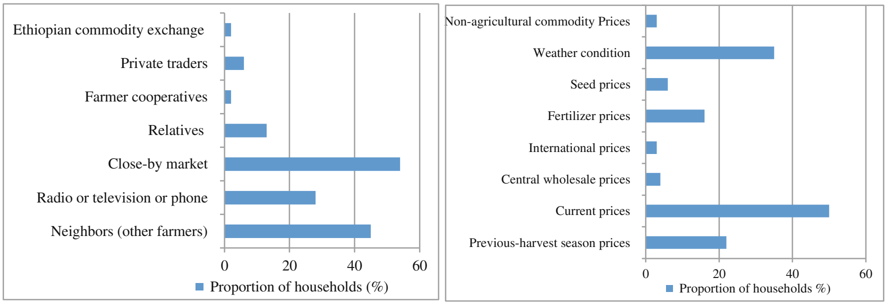


Fig. 20.1 Primary sources of price information (*left*) and relevant information for price expectation formation of smallholders (*right*) *Note*: respondents were allowed to give multiple responses

descriptive statistics also indicated that the Ethiopian Commodity Exchange (ECX) has not done enough to reach out rural smallholder farmers with price information.[5]

An interesting observation is that about half of the smallholders form their harvesting time price expectations based on the currently available price information. About a fifth of the respondents also considered prices from the past harvesting period in forming their price expectation. This may suggest that these households form their price expectations in line with the adaptive or naïve price expectation formation hypothesis. This is consistent with Chavas (2000), which indicated that close to half of the US beef markets were associated with the naïve expectation hypothesis. Nevertheless, other information such as weather, input prices, and central wholesale prices were reported by the smallholder farmers in our sample as relevant information in forming price expectation.

Subject to their access to information and their ability in data processing, farmers make their price predictions for the next harvesting period. The better the access farmers have to relevant price information, the more precise their price predictions are expected to be. This, in turn, results in a more efficient allocation of production resources. Table 20.2 presents the descriptive statistics for the smallholders in our sample, highlighting household characteristics, asset holdings, and other variables that could potentially affect farmers' data gathering and processing abilities that, in turn, influence their price expectation formations.

The summary statistics in Table 20.2 show a lot of similarities among the households from the four survey districts. On average, the household heads were in their mid-50s, and greater than two-third of them were married and male. The average family size (6.1) is slightly greater than the average household size in rural Ethiopia, which is 5.1 according to the household consumption and expenditure survey in 2010/2011 (CSA 2012). Although about 55 % of the overall household

[5]Established in 2008 as a partnership between market actors, members of the exchange, and the government, the ECX is a marketing system that, among other things, aims to disseminate real-time market information to all market players.

Table 20.2 Summary statistics of sampled smallholders by district

District	Debre Birhan		Ada'a		Kersa		Shashemene		Total	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Household characteristics										
Age of head	55	15	59	15	52	150	52	18	54	16
Female-headed HH (%)	30	46	31	46	35	48	29	46	31	46
Married HH head (%)	64	48	65	48	69	47	79	41	68	47
Family size	5.41	2.07	5.50	2.13	7.27	3.02	6.54	3.25	6.07	2.69
Years of schooling	1.36	2.56	1.75	2.92	1.24	2.16	3.65	4.43	1.90	3.18
Leadership position (%)	25	44	13	34	15	36	20	40	20	40
Discount rate	0.28	0.46	0.39	0.60	0.73	1.42	0.57	1.12	0.46	0.89
Asset ownership										
Total farm size (ha)	2.39	0.78	1.62	0.84	0.96	0.62	1.18	0.63	1.68	0.94
Per capita farm size (ha)	0.51	0.32	0.32	0.22	0.17	0.16	0.22	0.17	0.34	0.29
Radio ownership (%)	62	49	53	50	48	50	63	49	57	50
TV ownership (%)	1	11	23	42	4	21	12	33	8	28
Mobile ownership (%)	62	49	71	46	73	45	63	49	66	47
ICT ownership (mobile or radio or TV) (%)	80	40	81	40	79	41	80	40	80	40
Oxen ownership (%)	86	35	73	45	16	37	58	50	63	48
Tropical livestock unit (TLU)[a]	9.60	4.83	5.00	3.53	2.35	1.48	2.79	2.20	5.85	4.83

(continued)

Table 20.2 (continued)

District		Debre Birhan		Ada'a		Kersa		Shashemene		Total	
Variable		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Household asset (index)[b]		0.70	0.64	0.02	0.79	−0.89	0.82	−0.38	0.94	0.00	2.45
Farm income share (%)		91	13	87	22	95	17	96	1	92	16
Market share (%)		2	80	18	16	1	3	30	22	11	18
Access to market and other services											
Dist. to nearby grain market	km	10.36	3.11	11.45	1.61	6.81	3.33	8.73	3.65	9.46	3.47
	hr	2.05	0.62	2.28	0.49	1.73	0.95	1.64	0.82	1.94	0.76
Dist. to dry weather road	km	2.48	2.25	0.52	0.78	0.58	0.56	0.85	1.18	1.41	1.84
	hr	0.55	0.49	0.13	0.15	0.17	0.19	0.25	0.30	0.33	0.40
Dist. to all weather road	km	3.42	2.63	1.06	1.03	1.39	1.81	2.79	2.07	2.41	2.33
	hr	0.69	0.47	0.25	0.21	0.33	0.25	0.62	0.42	0.51	0.42
Dist. to extension agents	km	4.16	3.13	3.02	1.54	1.77	4.82	12.28	86.92	5.16	40.20
	hr	0.92	0.61	0.70	0.48	0.39	0.32	0.36	0.35	0.65	0.54
N		159		78		89		89		415	

Source: Survey data, 2013

[a]A tropical livestock unit (TLU) is an animal unit used to aggregate different classes of livestock. One TLU typically equals an animal of 250 kg live weight. We use 1 TLU to refer to 1 ox/cow, 0.75 bull/heifer, 0.45 calf, 0.15 goat/sheep, 0.5 donkeys, 1.15 horse/mule, 1.5 camel, and 0.005 for poultry (adapted from Ramakrishna and Demeke 2002)

[b]This is a weighted sum of all household assets except livestock and land computed by a principal component analysis

heads had some literacy skills through formal or informal education, the average family head had completed only the second grade. The smallholders in the sample had relatively large discount rates (46 %), which indicate severe liquidity problems. We measured discount rate using a survey question that elicits the minimum amount of money that a household head would have to be given in 6 months time in order to make them no different relative to a fixed amount given to them today.

The total land owned by the average smallholder was about 1.68 ha: smallholders in Debre Birhan district had, on average, slightly greater than 2 ha of land, whereas those in Kersa had slightly less than a hectare of land. The average per capita farm size was less than half a hectare. Besides, ownership of information assets such as mobile phone, radio, and television are very important in obtaining market, rainfall, and other information that could improve households' production decisions. The data showed that about 80 % of the smallholders owned at least one ICT tool.[6]

Other indicators of access to market and information include distances from basic facilities. For instance, smallholder farmers are located on average 3 km away from an all-weather road and 10 km from a nearby grain market. Thus, the average farmer needs to walk about 1 and 2 h to access these facilities, respectively. As agriculture is the main activity in all districts, it is not surprising that off-farm income contributes less than 10 % of the households' incomes. The degree of commercialization (market share of grains), as measured by the share of output sale from total production, is negligible in Kersa and Debre Birhan districts. This is mainly because *chat* is the main cash crop in Kersa, and sale of livestock is common in the latter.[7]

20.3.2 Empirical Model

We employed an econometric model to test part of the above theoretical model with the described household survey data. More specifically, we empirically assessed factors that determine the quality of the price signal, for example, whether households with better or cheaper access to information have more accurate price expectations. Our presumption was that a better price signal, as explained in the theoretical model, implies a more precise price expectation. To this end, we identified relevant variables that affect the precision of smallholders in their expectation formation. We obtained data on smallholders' expectations of harvesting season prices at planting time. This

[6]In this chapter, ICT ownership is the same as ownership of any of the three ICT assets, namely radio, television, or mobile phone.

[7]We calculated the market shares based on total sale and production of the six crops, namely teff, wheat, corn, sorghum, barley, and horse beans to be consistent with our empirical analysis.

allowed us to compute a deviation of farmers' expected prices (p^e) from realized harvesting period output prices (p^r or p_{t+1}) and use the deviation as a proxy for the quality of the price signal (i.e., as a measure of investment into information acquisition). Suppose PE denotes a measure of the price signal quality (henceforth prediction error), which is related to the variable V in the theoretical model. A simple model to explain prediction error for a typical farmer i can be specified as:

$$\mathrm{PE}_i = \alpha + \gamma \mathrm{ICT}_i + \theta M_i + X'\beta + \omega_i, \tag{20.7}$$

where PE is the deviation of each farmer's expected prices from the realized market prices—the outcome variable of interest; and the cost of information acquisition is captured by the two key variables of interest ICT and M. While ICT refers to ownership of information assets (radio, television, and phone), M refers to distance to markets. Both variables capture costs of acquiring information. X refers to a vector of all other explanatory variables that could potentially affect investment in information acquisition (and thus the level of precision in price expectation), such as household characteristics, discount rate, farm size, household wealth, and years of schooling; ω_i is an error term; and α, γ, β are parameters to be estimated.

As noted in footnote 6, we used ownership of the abovementioned ICT tools as one of the proxies for access to information. In other words, we expect farmers to use their radios, televisions, or phones to access better information on variables that influence harvest-time prices, suggesting beneficial effect on their price forecasting ability. There are at least two concerns with this assumption. First, it is possible that farmers use the ICT tools for purposes other than accessing information (e.g., for luxury purposes). Richer farmers, who tend to have more of these information assets, can have better price forecasts based on other channels. Second, there is a possibility that farmers who do not own these information assets share common intrinsic characteristics, such as poor farming skills and management abilities, which are unlikely to be affected by having better market information.

We have taken a few measures to account for these issues. First, we controlled for covariates, such as the level of education, age, wealth proxy variables, and other farmer characteristics, to take into consideration farming experiences and management abilities. Second, we controlled for a variable that captures access to price information, which is an interaction between ownership of ICT and whether farmers use any of the ICT tools as a source of price information. It is worth noting here that farmers may (and are expected to) use their information assets to access more than just price information. This in turn may affect their price prediction. Therefore, ownership of ICT tools remains our main explanatory variable of interest that serves as a proxy to "access to information." Lastly, we calculated household-specific average crop yield for our sample farmers using data from previous rounds of the Ethiopian rural household survey (ERHS). We specifically computed the average crop yield from the crop seasons of the ERHS data collected in 2004, 2009, and from our survey in 2013. If ownership of a radio, television, or mobile phone is systematically related to farming or management skills and ability, then we would expect farmers without these tools to have relatively low crop yields.[8] We included the average yield variable to control for these innate characteristics of farmers, which may also affect their price prediction error.

20.3.2.1 Measuring Prediction Error[9]

We used four alternative, but related, measurements as proxies for smallholders' price prediction errors (or accuracy). Suppose t and $t+1$ refer to the current sowing and the upcoming harvesting periods, whereby the former refers to the time of production decision. Therefore, t refers to the time when farmers form their price expectations for the period $t+1$. Suppose also that e denotes expectation; subscripts c, i, and v denote crop-, farmer-, and village-specific prices, respectively; n is the number of crops that a farmer grows and for which they report price expectations. The alternative measures of a farmer's price prediction error are defined as follows.

(a) *Absolute mean price prediction error (AMPPE)*
   We measured the AMPPE as the ***absolute mean*** deviation of the farmer's expected prices from the realized prices in the respective grain markets for n crops that the farmer grows

$$\mathrm{AMPPE}_i = \frac{1}{n}\sum_{c}^{n}\left(\left|p_{c,t+1} - p_{ic,t}^{e}\right|\right).$$

(b) *Relative mean price prediction error (RMPPE)*
   This is similar to the above measure except that we took the ***relative mean*** deviation of farmer's price expectations from the realized prices in the respective grain markets—instead of the absolute deviation.

$$\mathrm{RMPPE}_i = \frac{1}{n}\sum_{c=1}^{n}\frac{\left(\left|p_{c,t+1} - p_{ic,t}^{e}\right|\right)}{p_{c,t+1}}.$$

   The above two measurements assume that a farmer gives equal weight to each crop in his price expectations. However, a farmer may invest more in acquiring better information regarding a crop that he produces for a market compared to a crop that he produces for home consumption. This, in turn, affects his price prediction accuracy of the respective crops. To take this into account, we calculated the deviation of market share-weighted expected prices from

[8] A simple linear regression of ownership of assets on past average crop yield supports this statement: ownership is strongly and positively correlated with crop yield.

[9] In this study, we refer to the quality of farmers' price expectations—that is, the deviation of farmers' expected prices from realized prices—alternatively as price prediction error (accuracy), forecasting error (accuracy), and expectation error (precision).

similarly weighted realized prices. We used the market share of each crop to calculate price indices for each farmer and district. Using the farmers' reported and expected prices for sowing and harvesting periods, we obtain price indices for the respective seasons. Village-level price indices were similarly calculated using observed prices in the respective nearby grain markets. Furthermore, we normalized (both farmer- and district-specific) harvesting time price indices by the respective sowing time indices in order to consider the general trend of grain prices. Accounting for such price trends is important to overcome endogeneity in the estimation that may arise due to heterogeneities in the farmers' understanding of the overall inflation or deflation on their price predictions. Analogous to the two measures of prediction error mentioned above, we calculated the absolute and relative index price prediction error for each smallholder farmer.

(c) *Absolute index price prediction error (AIPPE)*
We calculated the AIPPE as an ***absolute*** deviation of ***indices*** of farmers' expected prices from the realized price ***indices*** in the respective markets/villages as

$$\text{AIPPE}_i = \left|\text{NPI}_{v,t+1} - \text{NPI}^e_{i,t}\right|,$$

where $\text{NPI}_t = \dfrac{\sum_c^n \alpha_c p_{c,t}}{\sum_c^n \alpha_c p_{c,t-1}}$ refers to the normalized price index—where the denominator (sowing period price) is normalized at 100—for each village v or for each household i. α_c refers to the market share of each crop.

(d) *Relative index price prediction error (RIPPE)*
RIPPE is calculated as the ***relative*** deviation of ***indices*** of farmers' expected prices from the realized price ***indices*** in the respective markets/villages.

$$\text{RIPPE}_i = \frac{\left(\left|\text{NPI}_{v,t+1} - \text{NPI}^e_{i,t}\right|\right)}{\text{NPI}_{v,t+1}}$$

Figure 20.2 illustrates how we measured PE using self-reported prices for the crops of interest in this study. The area in the dotted circle refers to realized (p_{t+1}) and expected (p^e) prices of the new harvesting period. The latter are price expectations of farmers made at sowing time, t. The graph in the right panel is a replication of the corn example for better illustration. The vertical distance between the realized and expected price, indicated by the red arrow line, is the prediction error.

The above measures of price prediction error combine multiple crops that a farmer grows. This might result in an "averaging-out" effect if a farmer who has a large expectation error for one crop tends to have a small error for the other. In other words, these measures are inadequate if a farmer's price forecasts have

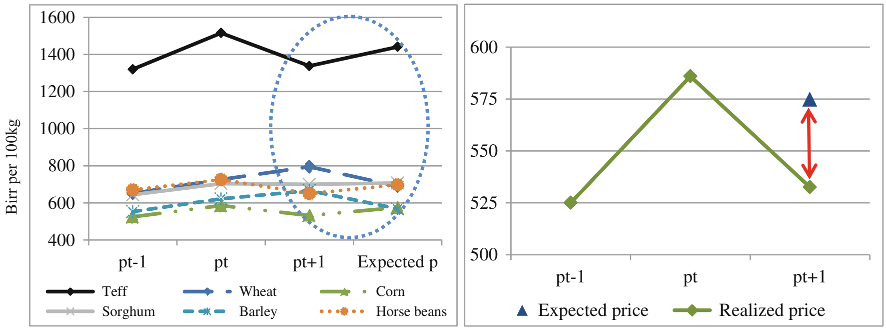


Fig. 20.2 Illustration of prediction error using self-reported prices

Table 20.3 Consistency of farmers' prediction errors between crops

Crop-to-crop errors	Reg. coef.	Corr. coef.
Barley and wheat	0.49*** (0.10)	0.38***
Corn and sorghum	0.82*** (0.16)	0.47***

Notes: Standard errors are in parentheses
** denotes statistical significance at the 1 % level or less

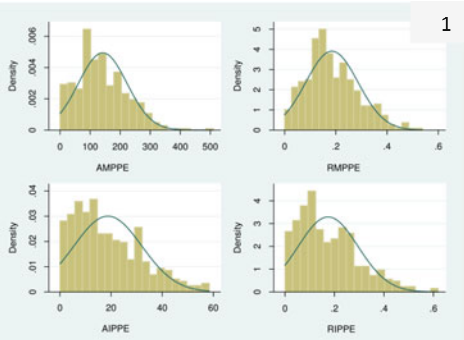
large discrepancies across different crops. In order to shed some light on this, we computed regression and correlation coefficients between the magnitudes of individual farmer's forecasting errors for corn to that of sorghum and for wheat to that of barley.[10]

The coefficients in Table 20.3 illustrate a significant degree of consistency in prediction errors between crops for the same farmer. The farmers who made large errors in their corn price prediction also tended to make large errors for sorghum. This is also true for the expectation errors of farmers growing both wheat and barley. This hinted that the mean deviation would not cause the error for one crop to be offset by the error for another, suggesting also that crop diversification would not lead to any better resource allocation for the farmer.

Moreover, the data showed that the crop-specific price forecasting (prediction) errors, on average, range between 19 and 20 % with comparable standard errors. This provided an additional clue for the absence of any large systematic difference in the difficulty of forecasting prices of different crops. There is also an economy of scale advantage for a farmer to invest in acquiring information on multiple crops.

[10]We chose these crops because of the larger number of farmers producing the respective crop pairs.

1



2

Variable	Original		IHS Transformed	
	Mean	(SD)	Mean	(SD)
AMPPE	141.84	(80.74)	5.38	(1.00)
AIPPE	18.73	(13.28)	3.28	(0.97)
RMPPE	0.18	(0.10)	0.18	(0.10)
RIPPE	0.17	(0.12)	0.17	(0.12)

Fig. 20.3 Summary statistics and distribution of the dependent variable

20.3.2.2 Estimation Technique

The nature of the dependent variable (price prediction error), an absolute value of a narrowly dispersed variable, requires paying special attention to the estimation method used. Because the prediction error has a zero lower bound, it has a positively skewed distribution (Fig. 20.3, Panel 1). This variable has a relatively small range, 0–0.6 with a mean close to zero, in the relative measures. As measured by RIPPE, for instance, the magnitudes of the prediction error made by smallholder farmers in our sample ranges from 0 % to as far as 60 %, with a mean value of 17 % (Fig. 20.3, Panel 2). This indicates that some farmers forecasted prices correctly, and the dependent variable has natural zero values. A quasi-maximum likelihood (QML) Poisson estimator would be appropriate in such situations (Cameron and Trivedi 2010; Nichols 2010; Wooldridge 2010). In fact, Santos Silva and Tenreyro (2006) argued that QML Poisson regression is preferred to an ordinary least squares (OLS) regression on a log-linear equation regardless of a count or a continuous dependent variable.[11] Because the mean and the variance of our dependent variables are not equal—that is, the distribution is not Poisson—we needed to use the robust sandwich standard errors (Cameron 2009).

An OLS estimation can be used if the residuals are normally distributed. We transformed the alternative dependent variables using the inverse hyperbolic sine (IHS) method to get residuals that are approximately symmetrically distributed.[12] We favored using IHS over logarithmic transformation as some households in our sample have zero prediction errors, the log of which is not defined.[13] The IHS is a logarithmic-like transformation that retains zero and negative values, unlike

[11]We refer to an interesting Stata Blog post by Bill Gould about using a Poisson regression model (http://blog.stata.com).

[12]The IHS transformation of variable x can be given as: $\text{ihs}(x) = \ln\left\langle \theta x + \left(\theta^2 x^2 + 1\right)^{1/2} \right\rangle$ and the scale parameter θ is assumed to be unity in most applications.

[13]Because the dependent variable (when measured in relative terms) is not a proportion where values above one are infeasible, a logit transformation is not needed for an OLS estimation.

logarithmic transformation, and has been applied in several studies (Bellemare et al. 2013; Burbidge et al. 1988; Moss and Shonkwiler 1993). This transformation allows us to interpret the OLS estimated coefficients as semi-elasticities. The marginal effects should be interpreted in percentage points in the case of the relative measures of the dependent variable (RMPPE and RIPPE).

20.4 Results and Discussion

Table 20.4 presents the estimation results of the maximum-likelihood Poisson regression model, specified as a generalized linear model (GLM) with a log-link function. The four columns differ in terms of the alternative measurements of prediction error, as discussed above. Although results are mostly consistent across the different specifications, we discuss the results from our preferred measure of prediction accuracy: the RIPPE. Besides accounting for the general grain price trend, this measure also weights crop prices with their respective market shares.

Controlling for access to ICT and grain markets, and other confounders, the estimated coefficients indicated that female-headed households had more accurate price expectations than male-headed households. Moreover, as expected a priori, households with an older (more experienced) head had statistically significant smaller forecasting errors. Not surprisingly, the precision of smallholders' price expectations was closely linked with the self-reported proxy for time preference (i.e., the discount rate). The results in Table 20.4 show that smallholders with higher discount rates, who tend to undervalue future gains and who therefore invest less in production but also information acquisition, have larger forecasting errors. This is consistent with the implication of the theoretical model.

As expected a priori, smallholders who had access to ICT such as radios, televisions, or mobile phones were more likely to make more precise price expectations than those who do not own any of these assets. Ownership of these assets enables them to access additional information on prices cheaply. More specifically, access to ICT was associated with about a 10 % decrease in the conditional mean of a smallholder's prediction error ($100 \times \left[e^{-0.11} - 1\right]$, in column [4] of Table 20.4). This means that the prediction error made by smallholder farmers who own any of the ICT tools was smaller by a factor of 0.89 than those who did not own any ICT tools, ceteris paribus. Smallholders who followed price information through radio or television or mobile telephony tended to forecast prices more accurately. This finding supports the theoretical model that indicates a negative impact of large information costs on the quality of the price signal. The interaction variable (ICT ownership and source of price information, $ICT \times InfoSource$) is not statistically significant in all specifications. This indicates that information assets might have improved a farmer's price prediction accuracy mainly through access to non-price information, such as weather.

Table 20.4 Factors that affect price prediction accuracy of smallholders

Dependent variable: relative mean/index price prediction error				
Variables	AMPPE	AIPPE	RMPPE	RIPPE
Male head	0.0328***	0.1089**	0.0353	0.1090**
	(0.0120)	(0.0460)	(0.0300)	(0.0430)
Age of head	−0.0004	−0.0027**	−0.0007**	−0.0026***
	(0.0010)	(0.0010)	(0.0000)	(0.0010)
Family size	−0.0108***	0.0054	−0.0112***	0.0067
	(0.0030)	(0.0110)	(0.0020)	(0.0100)
Head's years of schooling	0.0049	0.0001	0.0052***	−0.0008
	(0.0030)	(0.0060)	(0.0020)	(0.0050)
ICT	−0.0240	−0.1117***	−0.0557**	−0.1074***
	(0.0300)	(0.0410)	(0.0280)	(0.0260)
ICT × InfoSource	−0.0344	0.0885	−0.0207	−0.0724
	(0.0660)	(0.0610)	(0.0470)	(0.0620)
Past average crop yield	0.0090	−0.0525	−0.0028	−0.0478
	(0.0310)	(0.0600)	(0.0230)	(0.0370)
Share of farm income	0.0822	−0.0667	0.0587	−0.0429
	(0.0990)	(0.1690)	(0.1830)	(0.1810)
Market share	−0.0929	0.2323	−0.1631***	0.2591
	(0.0850)	(0.1460)	(0.0530)	(0.1700)
Per capita livestock value	−0.0177***	−0.0185***	−0.0158***	−0.0185***
	(0.0040)	(0.0050)	(0.0050)	(0.0050)
Per capita farm size	−0.0307	0.0061	−0.0043	0.0034
	(0.1320)	(0.1440)	(0.1490)	(0.1340)
Dist. to grain market	−0.0047	0.0301***	−0.0029	0.0296***
	(0.0030)	(0.0040)	(0.0070)	(0.0050)
Dist. to extension agents' office	0.0042	−0.0207	0.0032	0.0198
	(0.0130)	(0.0150)	(0.0100)	(0.0190)
Discount rate	0.0350***	0.0227***	0.0378***	0.0201**
	(0.0080)	(0.0070)	(0.0060)	(0.0090)
No. of crops	0.0706	−0.1092***	0.1038***	−0.1042***
	(0.0430)	(0.0350)	(0.0220)	(0.0260)
Constant	4.7818***	3.9814***	−1.7674***	−0.8357**
	(0.2980)	(0.6110)	(0.2040)	(0.3950)
District dummies	Yes	Yes	Yes	Yes
N	400	400	400	400

Notes: Standard errors are bootstrapped and clustered in seven *kebeles* (villages)
*, **, *** denote statistical significance at 10 %, 5 %, and 1 % level, respectively

We included two proxy variables for wealth, per capita value of livestock and farm size, to take into account any possibility that richer smallholders may have had better price forecasts using information from channels other than the aforementioned information assets. The results confirmed that (regardless of ownership of information assets) wealthier farmers have better price forecasts, as indicated by the statistically significant and negative estimated coefficient of the per capita value of livestock value. The lagged historical crop yield variable, which captures poor farming skills and management ability of farmers, turned out to be statistically insignificant. Although farmers who do not own ICT may share such common farmer characteristics, these innate characteristics did not have a causal effect on their price forecasting accuracy.

Another important factor which determines the cost of access to information is the proximity of households to major local grain markets. The empirical finding is consistent with the theoretical model: the costs of acquiring information were higher for households located farther away from grain markets. All other factors remaining constant, halving the "effective" distance to a nearby grain market reduces the forecasting error of a farmer who is located at an average distance away from the market by about 14 % ($100 \times \left[e^{-4.73 \times 0.03} - 1\right]$). This is consistent with the descriptive statistics as most households reported that they had usually visited nearby grain markets to obtain price information. In contrast, access to extension services—measured by distance from extension service offices—did not appear to be effective in providing information that helps smallholders improve their price forecasting performance. This may be partly explained by the training level of extension agents and the extent to which farmers trust the information they receive from agents.

We measured "access to ICT" by ownership of any of the information assets, namely radio, television, or mobile phone. It may, however, be necessary to investigate the differential impacts (if any) of each ICT. Table 20.5 presents the results using an exclusive ownership of mobile phone (column 2) and radio (column 3) as alternative measures of access to information.[14] Column (1) in this table is the same as the last column in Table 20.4, and the dependent variable is RIPPE in all cases. The results suggest that mobile telephony alone played a statistically significant role in improving the price forecasting accuracy of farmers. However, the marginal effect of exclusive ownership of mobile phones is smaller than the effect of our preferred measure of information access (an estimated coefficient of −0.05). Smallholders may use the information assets as a substitute or complement depending on several factors. The results also highlighted that ownership of a radio alone did not have a statistically significant effect on price prediction errors (column 3).

The last column in Table 20.5 controlled for interaction terms to test if the effects of access to ICT is conditional on some of the covariates (e.g., age and distance to market). Older household heads have more experience and are more likely to have better price forecasts, whereas younger heads do better if they have access to ICT. More specifically, the estimated coefficient of the interaction term of ICT and age of the head was positive (Column 4). The positive estimated coefficient of the

[14]Since only less than 10 % of our sample owns a television (8 %) or all three assets (7 %), we only consider exclusive ownership of a mobile or a radio as alternative proxies for access to ICT.

Table 20.5 Differential impacts of access to ICT on price prediction (RIPPE)

Variables	(1)	(2)	(3)	(4)
Male head	0.1090** (0.0430)	0.0937** (0.0440)	0.0973* (0.0520)	0.0957*** (0.0370)
Age of head	−0.0026*** (0.0010)	−0.0026*** (0.0010)	−0.0025* (0.0010)	−0.0092*** (0.0010)
ICT × Age				0.0088*** (0.002)
Family size	0.0067 (0.0100)	0.0036 (0.0060)	0.0032 (0.0060)	0.0054 (0.0060)
Head's years of schooling	−0.0008 (0.0050)	−0.0019 (0.0040)	−0.0013 (0.0040)	0.0021 (0.0040)
ICT[a]	−0.1074*** (0.0260)	−0.0513** (0.0230)	−0.0249 (0.0430)	−0.4494*** (0.1540)
ICT × InfoSource	−0.0724 (0.0620)			−0.0727 (0.0600)
Past average crop yield	−0.0478 (0.0370)	−0.0554 (0.0640)	−0.0521 (0.0700)	−0.0378 (0.0700)
Share of farm income	−0.0429 (0.1810)	−0.1386 (0.1690)	−0.1236 (0.1090)	−0.0027 (0.1510)
Market share	0.2591 (0.1700)	0.2433 (0.1930)	0.2406 (0.1590)	0.2594 (0.1630)
Per capita livestock value	−0.0185*** (0.0050)	−0.0182*** (0.0030)	−0.0174*** (0.0050)	−0.0199*** (0.0060)
Per capita farm size	0.0034 (0.1340)	−0.0222 (0.1530)	−0.0219 (0.1060)	−0.0036 (0.1260)
Dist. to grain market	0.0296*** (0.0050)	0.0296*** (0.0040)	0.0296*** (0.0040)	0.0417*** (0.0060)
ICT × dist. to market				−0.0145* (0.008)
Dist. to extension agents' office	0.0198 (0.0190)	−0.0164 (0.0100)	−0.0175 (0.0170)	−0.0218* (0.0120)
Discount rate	0.0201** (0.0090)	0.0184*** (0.0060)	0.0184*** (0.0070)	0.0204*** (0.0070)
No. of crops	−0.1042*** (0.0260)	−0.1078*** (0.0280)	−0.1109*** (0.0290)	−0.0970*** (0.0370)
Constant	−0.8357** (0.3950)	−0.7023 (0.5420)	−0.7423 (0.6500)	−0.6864 (0.6620)
District dummies	Yes	Yes	Yes	Yes
N	400	400	400	400

Notes: Standard errors are bootstrapped and clustered in seven *kebeles* (villages)
*, **, *** denote statistical significance a 10 %, 5 %, and 1 % level, respectively
[a]*Access to ICT* is measured as ownership of either a phone, radio, or TV in (1 & 4), only a phone in (2), only a radio in (3)

interaction term indicates that ownership of ICT tools has larger impacts on price prediction accuracy for households headed by younger farmers. This can be due to better knowledge of younger farmers with regard to using ICT tools and better understanding of the transmitted information.

Another interesting finding is that proximity to grain markets did not provide any more advantage in terms of predicting future prices as long as farmers have access to ICT. The estimated coefficient of the interaction term of ICT and distance from nearby grain markets was negative and statistically significant. In other words, the beneficial impact of ICT on price forecasting is stronger for smallholders located farther away from grain markets. Based on the estimated coefficients, the beneficial impact of access to ICT on price forecasting accuracy outweighs the detrimental impact of access to grain markets for farmers located as far as 15 km away from grain markets. This is because the interaction term indicates that prediction error increased by a factor of $e^{0.03} = \left(e^{0.04-0.01}\right) = 1.03$ for every kilometer increase in distance to markets (an increase by this factor for every 15 km is approximately equal to the decrease in prediction error because of ownership of ICT). This suggests that ownership of information assets can serve as an alternative way to gain access to market information for farmers residing far away from grain markets but not for those located more than 15 km away. Ceteris paribus, simultaneously providing access to ICT and halving the "effective" distance to nearby grain markets, improved the prediction accuracy of farmers by as much as 45 % ($100 \times \left[e^{\{-0.45+(-4.73\times 0.03)\}} - 1\right]$).

20.4.1 Robustness Checks

We estimated Eq. (20.7) using an OLS method on the IHS-transformed variables. The results are reported in Tables 20.7 and 20.8 in Appendix. The OLS results were largely consistent with the ML Poisson estimation results.[15] The control variables in our empirical model explained only a small but significant proportion of the variation in the farmers' forecasting errors.[16] Ethiopia is one of the countries in which agricultural commodity prices have experienced significant variability in recent years (Rashid 2011; Tadesse and Guttormsen 2011). High price volatility reduces the accuracy of producers' and consumers' forecasts of crop prices (Binswanger and Rosenzweig 1986), even though the impact is ambiguous in our theoretical model. Given the stochasticity of output prices, a lucky farmer gets his expected

[15]Note that comparison of OLS and Poisson regression coefficients is inappropriate as they are interpreted differently. One can calculate the average marginal effects, $\sum_i \frac{\partial E\left(y_i \middle| x_i\right)}{\partial x_{ij}} = \bar{y}\widehat{\beta}_j$, after the GLM regression and compare them with the corresponding OLS coefficients.

[16]The coefficients of determination, computed as a square of the correlation coefficients of the respective fitted and actual prediction error values, are comparable to the reported R-square in the OLS regression results.

price close to the actual value. Thus, the 'luck factor' could probably explain some of the remaining variation of smallholders' forecasting errors. There also appears to be a widespread exchange of price and other information among households, thereby suggesting that the private information of a farmer who has the most timely and relevant information could be open to the public domain.

As a further robustness check, we employed a maximum likelihood estimation (MLE) technique with normal distribution to simultaneously estimate the mean price and its heteroskedastic variance term. In the mean equation, the realized price was estimated using the (farmer-reported) expected price.[17] The residual $\varepsilon_i \sim N\left(0, \sigma_i^2\right)$ is the difference between expected and realized price. The variance of the residual is household-specific and normally distributed; it measures the forecasting error of the household. In the variance equation, the log variance was estimated conditional on the same set of explanatory variables X as before. Hence, the maximum likelihood regression reads:

$$p_{ic,t+1} = \alpha + \beta p^e_{ic,t} + \varepsilon_i, \tag{20.8a}$$

$$\ln\ \sigma_i = a_c + X'\gamma. \tag{20.8b}$$

The maximum likelihood estimation results are reported in Table 20.6. We first observed that farmers have unbiased price expectations (at least in the year of our survey) as α was not statistically different from zero. Furthermore, the results for the variance regression were mostly consistent with both the QML Poisson and OLS estimation results.

20.5 Conclusions

A time lag between production decisions and output realization is intrinsic in agriculture; therefore, price expectations play a crucial role in the production, marketing, and agricultural technology adoption decisions of a farmer. The literature widely explores the effect of access to information—in particular access to market information systems, and to information and communication technologies—on a variety of economic variables, at both a macro and a micro level. The current study complements the existing literature by investigating the role of access to information on the precision of smallholders' price expectations. Producers invest money and time in searching for price and other information, which they believe would improve their price expectations. This process is costly for an individual farmer. The cost of information is therefore crucial for farmers in deciding on their level of investment

[17]This approach relies on empirical tests for unbiased or rational expectations, as typically used for assessing efficiency on commodity markets. See, e.g., Algieri and Kalkuhl (2014). Rational expectations are usually tested against $\alpha \neq 0$ and $\beta \neq 1$.

Table 20.6 Factors that affect price prediction accuracy of smallholders, MLE

Variables	(1)	(2)	(3)	(4)
Equation 1: Observed market price (ln) is the dependent variable				
Farmer expected price (ln)	1.0076*** (0.0009)			
Constant	0.0048 (0.0039)			
Equation 2: Ln (sigma) serves as a proxy for the natural log of prediction error				
Male head	0.0649* (0.0338)	0.0560* (0.0335)	0.0563* (0.0335)	0.0712** (0.0343)
Age of head	−0.0024** (0.001)	−0.0023** (0.001)	−0.0022** (0.001)	−0.0034* (0.0019)
ICT × age				0.0011 (0.0022)
Family size	−0.0073 (0.0071)	−0.0118* (0.0068)	−0.0126* (0.0069)	−0.0107 (0.0072)
Head's years of schooling	0.0055 (0.0056)	0.0051 (0.0056)	0.0056 (0.0056)	0.0045 (0.0057)
ICT[a]	−0.0882** (0.0432)	−0.0664** (0.0302)	−0.0265 (0.0442)	−0.0946** (0.0409)
ICT × InfoSource	0.0198 (0.0343)			0.1682 (0.1842)
Past average crop yield	−0.0227 (0.0324)	−0.0230 (0.0321)	−0.0234 (0.0324)	0.0281 (0.0384)
Share of farm income	0.0653 (0.2000)	−0.0402 (0.1004)	−0.0207 (0.1002)	0.0713 (0.1126)
Market share	−0.0591 (0.1069)	−0.1112 (0.1055)	−0.1129 (0.1052)	−0.0882 (0.1099)
Per capita livestock value	−0.0120** (0.0061)	−0.0140** (0.0057)	−0.0135** (0.0057)	−0.0154** (0.0062)
Per capita farm size	0.0326 (0.0644)	0.0129 (0.0624)	0.0115 (0.0626)	0.0296 (0.0658)
Dist. to grain market	0.0080* (0.0045)	0.0084* (0.0045)	0.0087* (0.0045)	0.0336*** (0.0125)
ICT × dist. to market				−0.0277** (0.0129)
Dist. to extension agents' office	−0.0075 (0.0065)	−0.0047 (0.0066)	−0.0067 (0.0065)	−0.008 (0.0065)
Discount rate	0.0304 (0.0187)	0.0222 (0.0170)	0.0243 (0.0171)	0.0246 (0.0174)
No. of crops	0.2656*** (0.0159)	0.2668*** (0.0161)	0.2603*** (0.0157)	0.2670*** (0.0159)

(continued)

Table 20.6 (continued)

Variables	(1)	(2)	(3)	(4)
Constant	−2.3036***	−2.2150***	−2.2116***	−2.8668***
	(0.3390)	(0.2726)	(0.2747)	(0.3285)
District dummy	Yes	Yes	Yes	Yes
Wald chi2 test (*p*-value)	0.000	0.000	0.000	0.000
N	2394	2400	2400	2394

Notes: *, **, *** denote statistical significance a 10 %, 5 %, and 1 % level, respectively
[a]*Access to ICT* is measured as ownership of either a phone, radio, or TV in (1 & 4), only a phone in (2), only a radio in (3)

in information acquisition. In this study, we employed access to ICT and distance to markets as measures of costs of acquiring information. The theoretical model, which has been explained in Sect. 20.2, unambiguously showed that the level of farmer's investment in acquiring information is negatively influenced by the costs of accessing information.

Using a primary survey dataset that elicits smallholders' price expectations for the next harvesting period, we empirically evaluated the impact of access to ICT and grain markets and other variables of interest on smallholders' price prediction accuracy. The findings suggest that farmers who have access to ICT and who reside closer to grain markets have smaller forecasting error margins, supporting the implications of the theoretical model. This calls for improving the information and physical infrastructure in rural areas of the country in order to reduce costs of obtaining information. The beneficial effect of access to ICT was larger for households that reside farther away from grain markets and for those headed by relatively younger farmers. From a policy perspective, these differential impacts are compelling as younger farmers and farmers living farther away from grain markets are among the households that hold larger potential for increasing agricultural productivity in the country. This is because farm plots that are located very close to markets are highly degraded, and older farmers are less willing to adopt new technologies.

In agreement with the theoretical model, the empirical findings showed that farmers with higher discount rates were more likely to have larger forecasting errors. This has implications for assisting farmers in reducing future price and income uncertainties, and for enhancing their risk-management strategies. There are some institutions such as the Ethiopian Grain Trade Enterprise (EGTE), the Ethiopian Commodity Exchange (ECX), and the Agricultural Transformation Agency (ATA) that could potentially improve smallholders' access to market information in the country. These institutions may assist farmers in providing and disseminating reliable and timely central wholesale prices.

Access to extension agents did not have any statistically significant contribution to improving price prediction accuracy of farmers in our sample. Extension agents in Ethiopia serve more as a source of credit and inputs rather than a source of information on optimal input use and market information (Spielman et al. 2012).

Extension service, with agents who have valuable market information and better knowledge of how to use inputs than rural farmers, is important for improving the production decision of smallholders. However, past research has shown that Ethiopian extension agents have little practical experience and poor communication skills (Belay and Abebaw 2004). This could explain why farmers may not trust extension agents and hence do not adopt their advice. Because the Ethiopian government is expanding the extension service program throughout the country, it is important to consider disseminating reliable price and market information through extension services in the country to farmers with limited access to such information.

Acknowledgments We would like to thank Maximo Torero for his helpful comments on an earlier version of this chapter and for some crucial underlying ideas for the theoretical model framework. We also thank Justice Tambo, Jan Brockhaus, and Lukas Kornher for helpful discussions and Tobias Heimann for his assistance in the research. The authors are grateful for the financial support of the Federal Ministry of Economic Cooperation and Development of Germany (BMZ) for the research project "Volatility in Commodity Markets, Trade Policy, and the Poor" as well as for the financial support of the European Commission for the FOODSECURE project.

Appendix. OLS Estimation Results

Table 20.7 Factors that affect price prediction accuracy of smallholders

Dependent variable: relative mean/index price prediction error				
Variables	AMPPE	AIPPE	RMPPE	RIPPE
Male head	0.1121**	0.1590**	0.0059	0.0186***
	(0.0551)	(0.0622)	(0.0037)	(0.0043)
Age of head	0.0009	−0.0039*	−0.0001	−0.0004**
	(0.0014)	(0.0021)	(0.0001)	(0.0002)
Family size	−0.0068	0.0029	−0.0020***	0.0009
	(0.005)	(0.008)	(0.0006)	(0.0008)
Head's years of schooling	0.004	−0.0168***	0.0012***	−0.0004
	(0.0085)	(0.0060)	(0.0004)	(0.0006)
ICT	−0.0682***	−0.0435	−0.0102**	−0.0182***
	(0.0245)	(0.1080)	(0.0043)	(0.0068)
ICT × InfoSource	−0.0474	0.0176	−0.0028	0.0123
	(0.0757)	(0.1569)	(0.0097)	(0.0092)
Past average crop yield	−0.1102*	−0.0194	−0.0003	−0.0085
	(0.0613)	(0.1254)	(0.0064)	(0.0089)
Share of farm income	−0.1538	−0.0625	0.0085	−0.0092
	(0.2139)	(0.2765)	(0.0275)	(0.0298)
Market share	−0.1091	0.0273	−0.0308***	0.0328
	(0.1015)	(0.1788)	(0.0116)	(0.0315)

(continued)

Table 20.7 (continued)

Dependent variable: relative mean/index price prediction error				
Variables	AMPPE	AIPPE	RMPPE	RIPPE
Per capita livestock value	−0.0132*** (0.0051)	−0.0079 (0.0097)	−0.0031*** (0.001)	−0.0026*** (0.0007)
Per capita farm size	0.0044 (0.1041)	0.0264 (0.1234)	0.0001 (0.0245)	0.0009 (0.0254)
Dist. to grain market	−0.0158** (0.0076)	0.0261** (0.0130)	−0.0005 (0.0006)	0.0054*** (0.0012)
Dist. to extension agents' office	0.0111 (0.0151)	−0.0268 (0.0432)	0.0008 (0.0022)	−0.0039 (0.0033)
Discount rate	0.1011*** (0.0184)	−0.0376*** (0.0109)	0.0072*** (0.0014)	0.0031*** (0.0010)
No. of crops	0.1169** (0.0484)	−0.1324** (0.0520)	0.0208*** (0.0057)	−0.0169*** (0.0060)
Constant	6.1571*** (0.4752)	4.2603*** (1.1827)	0.1646*** (0.0623)	0.3296*** (0.0925)
District dummies	Yes	Yes	Yes	Yes
Wald chi2 test (*p*-value)	0.00	0.00	0.00	0.00
Root MSE	0.912	0.913	0.095	0.111
Adjusted R-square	0.20	0.15	0.15	0.20
N	400	400	400	400

Notes: Standard errors are bootstrapped and clustered in seven *kebeles* (villages)
*, **, *** denote statistical significance at 10 %, 5 %, and 1 % level, respectively. Note that since the dependent variable is either IHS-transformed (APPME & AIPPE) or expressed as a ratio (RMPPE & RIPPE), the coefficients can be considered as economically relevant

Table 20.8 Differential impacts of access to ICT on price prediction

Variables	(1)	(2)	(3)	(4)
Male head	0.0186*** (0.0043)	0.0164** (0.0070)	0.0169*** (0.0062)	0.0171** (0.0087)
Age of head	−0.0004** (0.0002)	−0.0004*** (0.0001)	−0.0004** (0.0002)	−0.0017*** (0.0002)
ICT × age				0.0016*** (0.0002)
Family size	0.0009 (0.0008)	0.0005 (0.0009)	0.0004 (0.0013)	0.0008 (0.0014)
Head's years of schooling	−0.0004 (0.0006)	−0.0006 (0.0006)	−0.0005 (0.0008)	0.0000 (0.0005)
ICT[a]	−0.0182*** (0.0068)	−0.0082* (0.0045)	−0.0047 (0.0050)	−0.0851*** (0.0233)

(continued)

Table 20.8 (continued)

Variables	(1)	(2)	(3)	(4)
Past average crop yield	−0.0085 (0.0089)	−0.0092 (0.0106)	−0.0086 (0.0080)	−0.0070 (0.0105)
Share of farm income	−0.0092 (0.0298)	−0.0263 (0.0284)	−0.0241 (0.0205)	−0.0046 (0.0284)
Market share	0.0328 (0.0315)	0.0326 (0.0285)	0.0324 (0.0270)	0.0332 (0.0212)
Per capita livestock value	−0.0026*** (0.0007)	−0.0026*** (0.0006)	−0.0025*** (0.0007)	−0.0028*** (0.0009)
Per capita farm size	0.0009 (0.0254)	−0.0022 (0.0259)	−0.0019 (0.0155)	0.0012 (0.0249)
Dist. to grain market	0.0054*** (0.0012)	0.0054*** (0.0009)	0.0054*** (0.0009)	0.0075*** (0.0015)
ICT × dist. to market				−0.0026** (0.0013)
Dist. to extension agents' office	−0.0039 (0.0033)	−0.0033* (0.0019)	−0.0035** (0.0016)	−0.0042** (0.0021)
Discount rate	0.0031*** (0.0010)	0.0029*** (0.0011)	0.0029** (0.0012)	0.0031*** (0.0010)
No. of crops	−0.0169*** (0.0060)	−0.0174*** (0.0048)	−0.0179*** (0.0061)	−0.0156** (0.0061)
Constant	0.3296*** (0.0925)	0.3473*** (0.0926)	0.3419*** (0.0784)	0.3666*** (0.1150
District dummies	Yes	Yes	Yes	Yes
Wald chi2 test (*p*-value)	0.00	0.00	0.00	0.00
Root MSE	0.111	0.111	0.111	0.111
Adjusted *R*-square	0.20	0.15	0.15	0.21
N	400	400	400	400

Notes: Standard errors are bootstrapped and clustered in seven *kebeles* (villages)
*, **, *** denote statistical significance at 10 %, 5 %, and 1 % level, respectively
[a]*Access to ICT* is measured as the ownership of either a phone, radio, or TV in (1 and 4), only a phone in (2), only a radio in (3)

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Coping with Food Price Shocks in Afghanistan

21

Anna D'Souza and Dean Jolliffe

21.1 Introduction

Elevated global food prices have eroded the purchasing power of households throughout the developing world, many of whom spend the majority of their income on food. Given the potential implications for poverty, health and nutrition, and the outbreak of food riots, the short- and long-term impacts of high food prices are of much concern to governments, nongovernmental organizations, and aid agencies. During the 2007/2008 food price crisis, many households were pushed into or kept in poverty (World Bank & International Monetary Fund 2012) and were forced to reduce the quantity and quality of food they consumed (International Fund for Agricultural Development 2008; Sanogo 2009). Field observations by the World Food Programme found that households also used nonfood coping strategies, such as migrating, selling assets, taking children out of school, begging, and selling land (Ruel et al. 2010).

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M. Kalkuhl et al. (eds.), *Food Price Volatility and Its Implications for Food Security and Policy*, DOI 10.1007/978-3-319-28201-5_21

Much of the literature has emphasized the impact of food price increases on poverty rates. A smaller set of literature has examined the impact on nutrition-related outcomes, such as undernourishment rates, calorie levels, and dietary diversity. Until now, little has been done to look at the implications of high food prices or food price increases on nonfood outcomes, such as nonfood expenditure or school enrollment. For the most vulnerable populations, living at or near subsistence levels, reducing the quality and quantity of food consumed, or cutting back on human capital investment (e.g., health and education expenditure) can have both immediate (e.g., wasting, increased illness) and long-lasting (e.g., stunting, intergenerational transmission of poverty) implications. More specifically, even short stints of poor nutrition can be detrimental to those with high nutritional needs like children, lactating and pregnant women, and the elderly (UNICEF 2009); and pulling children out of school could lead to long-term reductions in human capital accumulation since children are less likely to return to school after beginning to work (Guarcello et al. 2010).

In this chapter, we present evidence on household coping strategies from a nationally representative household survey collected in Afghanistan before and during the 2007/2008 food price crisis. These unique data come from the 2007/2008 National Risk and Vulnerability Assessment (NRVA) and cover over 20,000 households. During this period, due to a confluence of domestic (drought), regional (export bans), and international (food price crisis) factors, the price of wheat flour (the dietary staple) doubled. This represented a serious shock to Afghan households, who spend about 60 % of their budget on food and who derive over half their calorie intake from wheat. We look at how Afghan households adjusted their expenditure patterns on food and nonfood items. We look at changes in various dimensions of food security, including calorie, dietary diversity, and nutrient intake. The last two indicators reflect the quality of food consumed and are related to "hidden hunger," a term that refers to micronutrient deficiencies which have serious implications for long-term human capital formation. And we look at the purchase of food on credit, the sale of productive assets, school enrollment, and migration.

We found strong evidence that the wheat flour price increases affected the well-being of Afghan households, who reduced both their food and nonfood expenditures. The reductions in the value of food consumed were reflected in reductions in the quantity and quality of food consumed, including reduced nutrient intake. Households reduced their nonfood expenditures across several categories, including health, clothing, grooming, communication, transportation, cigarettes and tobacco, and culture. And households purchased food on credit more frequently. We failed to find changes in educational expenditure or school enrollment, the sale of productive assets, or migration.

Since much of food security policy is concerned with those living at or below subsistence levels, it is important to allow for the possibility that the behavioral responses of vulnerable households differ from other households in ways that are policy relevant. Therefore, the food security analysis allows for differential price effects based on a household's food security level. We used the UQR estimator, proposed by Firpo et al. (2009b), to identify price effects for households located at specific points on the unconditional distributions (such as the 20th or 80th quantiles) of the food security indicators.

The evidence indicated that Afghan households, across the distribution, experienced a decline in the quantity and quality of food consumed as a result of the 2008 wheat flour price increases. We found disparities in the behavioral responses of households with respect to where the household lies on the unconditional distribution of the particular food security measure of interest. Households at the top of the calorie distribution, who can afford to cut back, experienced the largest declines in per capita daily caloric intake. The most vulnerable households—that is, those at the bottom of the calorie distribution—cannot afford to make substantial cuts to their caloric intake since they are close to or below the minimum daily energy requirements; accordingly, we found no statistically significant decline in their caloric intake.

Households at the bottom of the dietary diversity distribution—often very poor households—experienced very large declines in dietary diversity as a result of the wheat flour price increases (although even households at the top of the distribution experienced substantial declines). The bottom households are likely unable to make major cuts to caloric intake and thus must adjust the compositions of their diet to maintain energy levels. Such declines can exacerbate already high levels of malnutrition in Afghanistan.

This chapter is an extended version of the study by D'Souza and Jolliffe (2014). It provides an additional analysis of nonfood-based coping responses (i.e., adjustments to nonfood expenditures and behaviors). For completeness, we included the main results from D'Souza and Jolliffe (2014), which examined food-based household coping responses. Our work contributes to the understanding of how the people of Afghanistan were affected by and how they coped with staple food price shocks, providing a rare insight into the short-term coping mechanisms in a poor, conflict country. Such analysis is particularly crucial in conflict countries, which may be most susceptible to shocks but for which usually very little quantitative data are available.

In the next section, we provide details on Afghanistan during the study period. We then discuss the evidence regarding food-based and nonfood-based household coping responses. Thereafter, we describe the household data, the variables of interest, and our sample. We then present the empirical specifications and estimation techniques. We next discuss the results and conclude the chapter in the final section with a discussion of the major implications.

21.2 Background: Afghanistan Circa 2007/2008

After decades of external and internal conflicts,[1] along with prolonged droughts, the landlocked Afghanistan has one of the poorest, least well-nourished populations in the world. Despite strong growth, with real GDP growth averaging approximately 10.8 % per year between 2003 and 2009, nearly 30 % of the Afghan population did not meet the minimum daily food requirements of 2100 kilocalories per person in 2008 (MoE Islamic Republic of Afghanistan and the World Bank Economic Policy and Poverty Sector 2010). The IMF (2009) estimated that the gross domestic product (GDP) per capita in Afghanistan was $350 in 2007 and $457 in 2008 (current US$).[2] Based on a broader set of development indicators used in the UNDP Human Development Index (e.g., health, education, living standards), Afghanistan ranked 181 out of 182 countries in 2008 (UNDP 2009). Approximately 60 % of children under five suffered from chronic malnutrition (stunting), and 8 % suffered from acute malnutrition (wasting) (Johnecheck and Holland 2007).

The Afghan economy is largely based on agriculture; major crops include wheat, rice, maize, barley, vegetables, fruits, and nuts. Approximately 70 % of cultivated crop area is devoted to wheat, and about 15 % is devoted to rice, barley, and maize (Chabot and Dorosh 2007). Wheat is both a major production crop and the main staple of the Afghan diet, contributing to 54 % of the total caloric intake. Due to violence and large fluctuations in weather, however, wheat production is highly volatile, and the country is dependent on its trading partners to meet any shortfalls. Pakistan is Afghanistan's major supplier of wheat (mostly in the form of flour) due to close historical ties and a shared 1600 km border; Pakistan's share of the Afghan wheat and wheat flour import market is estimated to range from 59 % (Chabot and Dorosh 2007) to 79 % (Maletta 2004).

Levels of food insecurity vary greatly across the country, which is not surprising given Afghanistan's diverse terrain, climate, and agricultural zones. Seasonality plays an important role in food security in Afghanistan. Temperatures can vary dramatically across seasons, with hot summers and frigid winters, and the climate in the highlands varies with elevation. In many cases, severe winter conditions affect transportation, and in high mountainous areas, roads are often blocked throughout the winter due to heavy snow accumulation.

According to the World Food Programme, Afghanistan is among the world's most vulnerable countries in terms of absorbing food and fuel price shocks; such

[1] Afghanistan has a long history of conflict involving both intra- and interstate groups; for an overview of the conflict over the past 30 years, see Giustozzi and Ibrahimi (2012). In this chapter, we do not distinguish between different actors; rather we define conflict based on incidents of violence in which there are fatalities and/or casualties; more details are provided in the data section.

[2] In a country like Afghanistan though, where the drug economy is large, the official National Income Accounting data are likely to significantly understate GDP. UNODC (2008) estimates that in 2007 the farm gate value of opium cultivation was US$1 billion, but this dropped to US$730 million in 2008. The potential export value in 2007 of opium, morphine, and heroin at border prices in neighboring countries was $4 billion (or, in per capita terms, about $160).

countries have consistently high levels of food insecurity, are heavily dependent on food and fuel imports, and have large populations of poor people who spend significant shares of their income on food (Sanogo 2009). Also, mountainous terrain and poor infrastructure, coupled with weak governance, insecurity, and corruption, have limited the government's ability to manage its food distribution and supply networks.

International prices of food commodities increased substantially in 2007 and rapidly in early 2008, peaking around May–July 2008. During this period, Afghanistan experienced several shocks that led to a disruption of its food supply network, causing prices to soar throughout the country. Due to drought and early snow melt, the 2008 wheat harvest of 1.5 million metric tons was the worst since 2000 (Persaud 2010). The price impact of the large shortfall in wheat production was magnified by export bans in Pakistan and rising international food prices. In February 2008, the Afghan government eliminated import tariffs on wheat and wheat flour (tariffs had been set at 2.5 %), but due to export bans in Pakistan, Iran, and Kazakhstan, the action brought about little downward effect on prices. Between fall 2007 and summer 2008, the prices of domestic wheat flour increased by over 100 %; Figure 21.1 displays retail wheat flour prices from 2002 to 2013 for four major urban centers collected by the FAO Global Information and Early Warning System (GIEWS).

In 2007/2008, total inflation was largely driven by the surge in food prices; Figure 21.2 depicts the consumer price indices (CPI) for food and nonfood items in urban areas from 2005 to 2011.[3] During the survey time frame

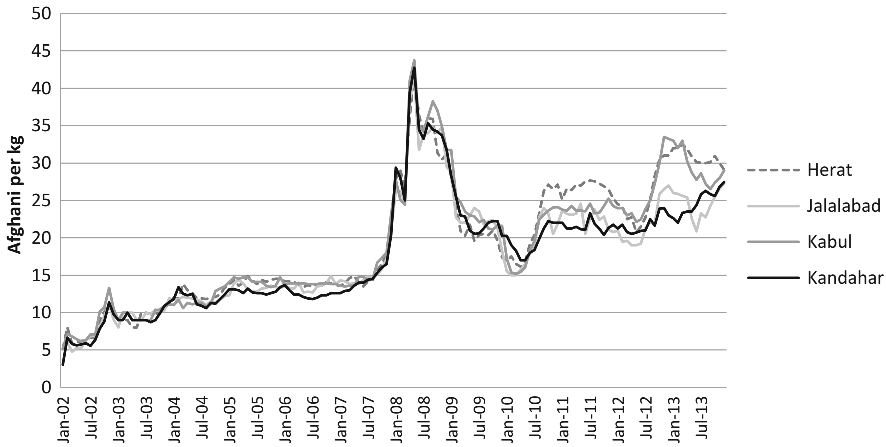

Fig. 21.1 Retail wheat flour prices, 2002–2013. *Source*: FAO GIEWS (2014)

[3]The indices were constructed by the Afghan Central Statistics Organization and are based on data from six urban areas.

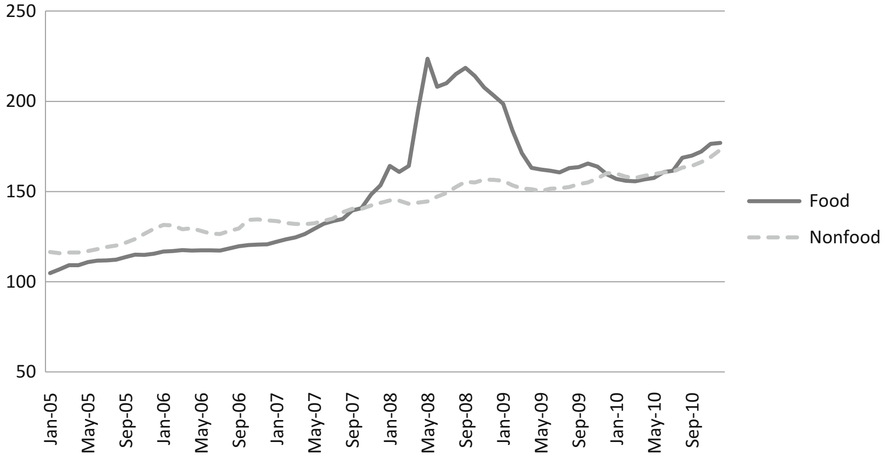

Fig. 21.2 Consumer price indices, 2005–2011

(August 2007–September 2008), the urban food CPI increased by nearly 60 %, while the nonfood CPI increased by only 10 %. Our calculations using price data collected in the NRVA also indicated a 60 % increase in food prices in urban areas during this period, with an overall increase of 40 % at the national level.

21.3 Household Coping Strategies

In response to price shocks or, more generally, negative shocks (e.g., income shocks, drought or natural disaster, death of main income earner), households employ a variety of coping strategies or responses. They may rely on family assistance, sell off assets, work more, borrow money, or—in the most desperate cases—reduce intake of food and nutrients. Such responses can be characterized as nonfood based or food based, and families can employ one or both of them (FAO 2008). Increases in food prices represent a decline in purchasing power for households.[4] Nonfood-based coping strategies to deal with the reduced purchasing power include increasing time spent working for adults (and, in some cases, children); reducing expenditure on health, education, and other nonfood items; and changing household composition (e.g., migrating or sending children to live with relatives). In some instances, households remove children from school to save on school fees and to use the children as labor (at home, on the farm, or in the marketplace). Food-based coping strategies include changing the type and quantity of food a household consumes and the people who consume the food in a household. Households may

[4]Below we discuss the potential income effect of increasing food prices for households that are net sellers of food.

reduce the quantity (e.g., smaller meals, less frequently), quality, and diversity of foods consumed by moving toward cheaper food groups and cheaper foods within food groups.

Some of these strategies are reversible; for example, if prices decline, households can go back to purchasing higher-quality food. But other strategies are irreversible; for instance, after selling off productive assets, households may not be able to repurchase them even when food prices decline (Hadley et al. 2012). Furthermore, some of these responses can have long-term consequences for health and human capital development. For example, disinvesting in children (with respect to nutrition and/or schooling) can perpetuate the intergenerational transmission of poverty. Moreover, with over two billion people estimated to be suffering from mineral and vitamin deficiencies worldwide (Micronutrient Initiative and UNICEF 2009), further reductions in nutrition can have deleterious effects on households living below or near subsistence levels.

In this section, we discuss the current literature on food-based and nonfood-based coping responses to high food prices. (See Ruel et al. (2010) for a more detailed review of the literature on the effects of economic crises on well-being, and see Compton et al. (2010) for a thorough review of the literature on the impacts of the 2007/2008 food price crisis.) Most recent studies on high food prices examined the implications for poverty rates rather than specific household coping responses. The studies often relied on data collected during periods of relatively stable prices and used the limited variation in prices to estimate price elasticities. Then these studies used simulation models to estimate the short-run effects of larger price shocks on measures of household welfare, primarily poverty rates, with many studies focusing on differences between outcomes for rural and urban areas. Examples of such studies include Wodon et al. (2008), who examined 12 African countries; Ivanic and Martin (2008), who examined nine low-income countries; Ul Haq et al. (2008), who examined Pakistan; Simler (2010), who examined Uganda; Robles and Torero (2010), who examined four Latin American countries; and De Hoyos and Medvedev (2011), who examined 73 low- and middle-income countries. In those studies, the magnitude of the impact of the crisis varied greatly among households and countries, and it depended on several factors, including the degree of price transmission, dependence on food imports, whether staple foods are traded internationally, whether the household is a net buyer or a net seller of food, and the household's reliance on staples. But the general finding was similar: national poverty rates increased, with urban areas on average suffering larger increases.

With this chapter, we are contributing to a smaller set of literature that examines the impact of recent high food prices on nutrition-related outcomes. Using data from eight developing countries, Anríquez et al. (2013) simulated the effects of staple food price increases on household undernourishment (defined as falling below daily calorie thresholds) for the average household, for urban and rural households, and by expenditure decile. The study showed that mean calorie levels generally declined with increasing staple food prices; however, countries varied in terms of the people who were the most negatively affected (e.g., poorest or middle quintiles, rural or urban populations) and in terms of the household-level determinants of the nutritional responses. Tiwari and Zaman (2010) also found that undernourishment rates increased across all major developing country regions assuming minimal levels of price transmission from international to domestic markets. Brinkman et al. (2010) looked at the impact of high food prices (and the global financial crisis) on food consumption, nutrition, and health outcomes for specific developing countries as well as several developing regions. Bibi et al. (2009) found that food poverty and undernourishment increased among children in Mali. In a study of rural Bangladesh, Torlesse et al. (2003) found that as rice prices fell, households reduced rice expenditure and increased non-rice food expenditure, thereby improving the quality of their diets. Klotz et al. (2008) provided a more nuanced view that households are likely to reduce the quality of food consumed before reducing the quantity of food consumed, and for this reason, individuals will experience micronutrient deficiencies before weight loss.

We are also contributing to the literature (including qualitative and quantitative studies) that examines nonfood-based coping responses (often in addition to food-based ones) to increases in food prices. Compton et al. (2010) examined the literature and summarized the variety of nonfood-based coping strategies, which include reducing nonfood expenditure, pulling children out of school and increasing child labor, planting more food crops, increasing labor, increasing migration, selling nonproductive or productive assets, going into socially unacceptable livelihood activities (such as begging), and receiving increased aid from the government or nongovernmental organizations. Tandon and Landes (2014) found that in response to food price increases, Indian households decreased dietary diversity and delayed the purchases of health-related goods, clothing, and durable goods.

Sulaiman et al. (2009) showed that households in Bangladesh cut back on the number and quality of meals when food prices increased; they also found that households reduced expenditure on clothing, health, transportation, and cooking fuel. Looking at households in Somalia, Holleman and Moloney (2009) found reductions in nonfood expenditure (including money spent on medicine), increases in financial assistance (e.g., remittance, cash gifts, loans, credit purchases), and a drop in school enrollment. They also found that households switched to cheaper foods, for example, from imported rice to locally produced sorghum. And finally, Hadley et al. (2012) provided qualitative evidence from urban Ethiopia that increases in food prices can have an impact on important cultural practices, such as funerals, because households can no longer afford standard cultural practices at their socioeconomic level.

In studies based on simulation models, it is largely impossible to identify separately the extent to which the simulated estimates resulted from actual changes in household well-being or from modeling assumptions. Most studies have focused on the short run, assuming that (1) households and producers have no behavioral responses to the price increases, (2) there are no changes in input prices or wage rates, and (3) the proportional changes in consumer and producer prices are equivalent. In a recent contribution, Minot and Dewina (2013) demonstrated the sensitivity of poverty results to these standard assumptions.

The need to simulate the welfare effects of a price increase is driven (partially) by a lack of comparable data before and after the price increase. Our study represents one of a handful of empirical analyses that have overcome the need to simulate welfare effects by using nationally representative household data collected prior to and during a significant price shock. Friedman et al. (2011) used nationally representative data from Pakistan to estimate reductions in calorie availability due to the 2008 food price spike and found an 8 % reduction between 2006 and the first half of 2008. They also found that rural households with access to agricultural land fared better than urban households. Examining the same price spike and using nationally representative rural household data from Bangladesh, Balagtas et al. (2012) found an increase in poverty rates and demonstrated that the determinants of poverty change over time. And using nationally representative data from South Africa, Jacobs (2010) found that household hunger levels increased as a result of the food price and financial crises of 2007–2009. These studies employed various other methodologies and focused on different household-level outcomes, but like the present chapter, they were all able to observe (and estimate) behavioral responses to large increases in food prices (given the available data) rather than through modeling assumptions or simulations.

21.4 Data

Our primary data are from the NRVA 2007/2008, which was conducted by Afghanistan's Central Statistics Organization and Ministry of Rural Rehabilitation and Development. The survey was administered between August 2007 and September 2008 and covered over 20,500 households (over 150,000 individuals) in 2572 communities in all 34 provinces of Afghanistan. The long time frame made it possible to obtain seasonally representative estimates of household food security and allowed for the coverage of conflict areas.

The sample was selected based on a stratified, multistage design. The survey was stratified explicitly, geographically, and implicitly over time.[5] The 11 provinces with the most populous provincial centers were each stratified into urban and rural areas. The remaining provinces were treated as separate rural strata, and the nomadic Kuchi population was treated as a separate stratum. The stratification resulted in 46 domains or strata. In the first stage of selection, 2441 primary sampling units (PSU) from urban- and rural-settled populations and 131 PSUs from Kuchi populations were drawn. In the second and final stage, eight households were selected from each PSU.

The implicit stratification over time was a key element of the survey design. The population frame was sorted both spatially and temporally to ensure that (with a systemic interval selection) the selected sample would be seasonally

[5]The population frame is based on a 2003–2005 national household listing.

representative.[6] Thus each quarterly sample of the NRVA survey is representative at the national level. In a country where agriculture is an important form of livelihood, seasonal variations in consumption patterns are to be expected; thus it is critical to capture nationally representative measures of household food security throughout the year. Appendix Table 21.10 displays key demographic, educational and health, and infrastructure indicators across the four quarters. While we observed some statistical differences in means across quarters, there is little evidence of systematic differences in the samples based on these generally time-invariant characteristics.

Another key feature of the survey was the yearlong fieldwork, which allowed for coverage of conflict-affected areas. The enumerators informally secured permission from local leaders in conflict areas, and when a primary sampling unit (PSU) was considered too dangerous to interview at the scheduled time, it would be reconsidered at a later date within the quarter, instead of being replaced immediately. This flexible design helped to ensure a low replacement rate. While the majority of replacements were due to security issues, only 68 PSUs were replaced from the planned 2441 PSUs in the sample design (less than 3 % replacement rate).[7] It is often difficult to obtain reliable data from conflict areas; thus the current analysis provides a rare insight into the relationship between food insecurity and conflict.

The household survey module includes 20 sections—6 administered by female interviewers to female household members and 14 administered by male interviewers to the male household head. The enumerators traveled in teams of two (one male and one female) since females are not able to travel by themselves in Afghanistan and because it is important that interviews be conducted between individuals of the same sex due to the strong cultural norms regarding separation between the sexes outside the family. Households were asked questions about consumption, demography, housing infrastructure and access, maternal and child health, education, income sources, agriculture and livestock, migration and remittances, and assets and credit.

To collect data on nonfood expenditure, respondents (male and female, depending on the category) were asked about the amount of afghani spent on various items or categories of items over the past month or year (depending on the category). Below we describe how we constructed the nonfood expenditure measures; in the caveats section, we discuss potential biases that could result from the various recall periods.

The food consumption data include the frequency and quantity of consumption of 91 food items over the previous week, including food bought on the market, produced, or obtained through other methods like food aid or gifts. The NRVA's broad coverage of foods, including seasonal varieties, allows for better calculation of caloric and nutrient intake than surveys which take fewer items into account.

Household consumption data do not typically account for food wastage, and thus estimates of food intake may be larger than actual values. We assume that in a poor country like Afghanistan, wastage is relatively small and therefore not a significant

[6]See Kish (1965, pp. 235–236) for a discussion of implicit stratification.

[7]Replacement PSUs were primarily selected from the nearest secure district.

source of bias. Generally, in low-income countries like Afghanistan, much less food is wasted at the consumer level than at early and middle stages of the food supply chain (FAO 2011). A potentially more challenging concern is if wastage is correlated with price volatility. If the amount of food wasted is negatively correlated with food prices (as might be expected), then the coefficients of the price of wheat flour in the regressions that examine food consumption and caloric intake will have positive biases.[8] However, we maintained the assumption that wastage is low and any potential bias is small.

The price data were obtained from a district price survey, which included prevailing prices of the food items included in the consumption section as well as domestic and imported grains and fuel. The local price data were important for obtaining accurate estimates of price effects in a mountainous country with poor infrastructure, where transportation and transaction costs vary greatly.

Finally, we also used confidential geo-coded conflict data obtained from the United Nations Department of Safety and Security (UNDSS) that cover the survey time frame from August 2007 to September 2008. The UNDSS collects information on fatalities, injuries, and, in general, violent incidents. According to the official UN definition, violent incidents include the following: abduction, air strike, armed clash, arrest, assassination, finding a weapons' cache, confrontation/dispute, crime, demonstration, IED (improvised explosive device) detonation, finding an IED, information, intimidation, mine/UXO (unexploded explosive ordnance) incident, narcotic incident, standoff attack, suicide attack, and others. Over the survey year, there were 506 violent incidents across the country, with 421 associated fatalities and 322 associated injuries.

21.4.1 Measures of Nonfood-Based Coping Responses

Our main measures of nonfood-based coping responses were nonfood expenditures. We constructed a measure of real per capita monthly nonfood expenditure, total expenditure, and expenditure for eight major categories: health, education, clothing (including shoes), grooming (including laundry fees), tobacco and cigarettes, transportation, communication, and culture.[9] We also constructed several complementary measures: recent migration of household members, selling of livestock (which are productive assets), enrollment of children in school (at the individual level), and a categorical variable denoting the frequency with which households report buying food on credit (1–4: never, sometimes, often, and always). We classified the last

[8]The sign of the bias is determined by the product of the correlation coefficients of (1) food waste and wheat flour prices and (2) food waste and food expenditure or caloric intake. If both correlation coefficients are negative, then their product, and thus the sign of the bias, is positive.

[9]The recall period for grooming, tobacco and cigarettes, and communication expenditures is the past 30 days. The recall period for health, education, clothing, and culture expenditures is the past 12 months.

measure as nonfood based because it relates to credit and debt rather than changes in actual food consumption. Alternatively, one could classify this measure as a food-based coping strategy. In this chapter, however, we adopted the FAO categorization, in which food-based coping strategies correspond to changes in the quantity or quality of food consumed (FAO 2008). To convert nominal values into real values, we used the nonfood price index from the Consumer Price Index for Afghanistan. The index accounts for temporal, but not spatial, differences in prices.

21.4.2 Measures of Food-Based Coping Responses

We constructed three main measures of household food-based coping responses for use as dependent variables in the regression analysis: food consumption, per capita daily caloric intake, and household dietary diversity. The first, real monthly per capita food consumption is an informative measure of household well-being and a core component of poverty indicators. It has been used as a measure of food security in the literature as well; for an early example, see Green and Kirkpatrick (1982). The second is a widely used measure of health and undernourishment. And the third has been shown to be linked to the nutritional status of children and adults (Arimond and Ruel 2004; Ruel 2003; Steyn et al. 2006) and has been lauded as a cost-effective, quick, informative measure of food security (Headey and Ecker 2013; Tiwari et al. 2013). Although much of the economics literature has focused on caloric intake as a nutritional measure and a measure of food security, there is a growing recognition of the importance of dietary quality to short- and long-term health, cognition, and productivity outcomes; therefore, we incorporated and highlighted measures of dietary quality in our work.

The real value of food consumption (in afghani) is calculated by combining quantity data from the consumption module with price data from a district price survey. Food consumption data include food which was bought, produced, or obtained through other methods, e.g., food aid and gifts. Weekly values were multiplied by 4.2 to get monthly values. Prices were matched by month, item, and district. Since not all food items were available in all district markets at all times of the year, we imputed the missing elements to obtain a complete price matrix.[10] We calculated average prices for domestic and imported varieties separately to account for differences in price and quality between domestic and imported wheat and rice.[11] The value of the expenditure on food away from home was included in the

[10]The imputation process filled in missing values using the first-feasible methodology according to the following order: (1) median of the 20 nearest neighboring districts of that month, (2) province median of that month, (3) national median of that month, (4) median price of 20 neighboring districts of the quarter, (5) province median of that quarter, and (6) national median of that quarter.

[11]The survey includes questions about the percentages of imported wheat and rice consumed; these percentages were used to calculate the total expenditure on these items.

calculation of food consumption, but it was not included in the calculation of caloric intake since quantity data on such food were not collected.

We adjusted the food consumption estimates to take into account spatial and temporal variation in prices in order to identify correctly those households that fall below the food poverty threshold (described below) and, in the regression analysis, to estimate the impact of the price increases on real values. We used a Laspeyres price index estimated by quarter for each region. The food price index was based on a reference bundle of goods consumed by relatively poor households; the reference bundle was constructed to reflect regional diversity in consumption patterns. There are eight regions in Afghanistan, as defined in Islamic Republic of Afghanistan and World Bank (2011). Real food consumption is relative to the chosen base: urban areas in the Central Region in quarter 1; the capital, Kabul, is located in the Central Region.

We used the FAO Food Composition Tables for the Near East to convert daily food quantities into kilocalories; we then divided the daily caloric intake by the effective household size to get the per capita daily caloric intake.[12] The effective number of household members incorporates guests eating meals within the home and decreases when household members do not regularly take meals at home.[13] The effective number of household members is greater than the household size for the richer households and lower for the poorer households.

To measure household dietary diversity, we used the food consumption score (FCS), which is developed by the World Food Programme (WFP) and used in food security assessments throughout the world. It is a weighted sum of the frequencies with which households consume foods within eight food groups over the previous week.[14] The food groups include grains, pulses, vegetables, fruit, meat/fish, milk/dairy, sugar, and oil/fat. Higher scores denote a more varied diet and are suggestive of a higher-quality diet with a potential for higher micronutrient intake.

It is challenging to account for food consumption and expenditure on meals away from home. The survey asked how many meals were eaten away from home by household members over the past 7 days and the value of food and drinks consumed outside the home over the past 30 days; however, there was no information on

[12]Spices, water, and "other" foods do not contribute to total calories. USDA sources were used for a few items that were not available in the FAO tables.

[13]Some studies use household size to calculate per capita amounts, but the prevalent custom of sharing meals in Afghanistan makes it important to account for guests eating meals from the household cooking pot. We do not use equivalency scales to account for differences in consumption of adults and children when calculating measures of well-being but rather opt to include variables for household composition directly into the regression model to control for such differences.

[14]Weights for the food groups range from 0.5 to 4 based on nutrient density. Condiments receive zero nutritional weight. Frequencies are truncated at 7 for each food group. The measure ranges from 0 to 112.

what food is consumed outside the household.[15] Therefore, we did not include any calories from food eaten away from home in the caloric intake calculation, and food consumed away from home also did not impact the food consumption score. These measures may not accurately capture all food consumed by members of the household. Without detailed food diaries however, it is difficult to obtain sufficient information. Note that food away from home constituted about 2 % of total food expenditure on average; it accounts for less than half a percent for the poorest 20 % of the population and about 4 % for the richest 20 % of the population.

21.4.3 Summary Statistics

The effective sample size of our analysis was 20,483 households.[16] Table 21.1 displays the population means of key household characteristics for the full sample over the survey year. On average, households had 8.6 members living in about 3.6 rooms (or tents for the Kuchi population). A typical household consisted of 2.1 men, 2 females, and 4.5 children (under 16). The head of a household was on average about 45 years old; nearly all were married, and most of them were illiterate. Approximately 80 % of the households resided in rural areas. Very few households reported having members who migrated or reported selling livestock recently (over past year). Finally, about 16 % of the households reported that they were often or always purchasing food on credit; the remainder of the households reported that they had never (27 %) or sometimes (57 %) purchased food on credit. Approximately 59 % of the households reported borrowing money over the prior year; and 70 % of those households reported that the money was used mainly to purchase food.

Table 21.2 displays the population means for the total nonfood and the total food expenditure as well as caloric intake and dietary diversity by quarter and for the survey year. The raw data revealed the instability of household food security in Afghanistan; we observed large declines in food expenditure, caloric intake, and dietary diversity, with the worst levels observed in quarters three and four. Changes in nonfood expenditures were less stark, although the nonfood expenditures on many categories declined over the survey year. Overall, these patterns lend support to the evidence that the poverty rate had increased, as reported by the Government of

[15] We use the questions on meals eaten outside the home and the value of food and drinks consumed to calculate average expenditure on food away from home for each household, which is included in the total value of food consumption.

[16] The household response rate was 99.8 %, and the PSU replacement rate was 3 %. Thirty-two households were dropped due to missing female questionnaires; all of these households were located in four communities, suggesting a relatively small systematic error in field operations. Fifty-two households were dropped due to missing consumption data, and seven households were dropped due to missing asset data. Information on household size was missing for one household, and therefore, the household was dropped because per capita measures of consumption and food security could not be calculated.

Table 21.1 Household characteristics

Age of household head	44.87
Number of males	2.09
Number of females	2.01
Number of children under 16 years	4.51
Share of households with married head	0.95
Share of households with literate head	0.32
Share of agricultural households	0.57
Share of households in rural areas	0.80
Share of households in plain areas	0.74
Share of households in plateau areas	0.22
Share of households in mountainous areas	0.39
Share of households with recent migrant	0.08
Share of children between 8 and 16 years in school	0.95
Share of households purchasing food on credit often or always	0.16
Share of households that sold live livestock recently	0.03
Total observations	20,483

Source: NRVA 2007/2008. *Note*: Estimated population-weighted means. Share of children in school is derived from individual child-level data set with 35,893 observations

Table 21.2 Population statistics by quarter and over survey year

Real per capita monthly expenditure (afghani)	Quarter 1 (fall)	Quarter 2 (winter)	Quarter 3 (spring)	Quarter 4 (summer)	Survey year
Total	2022.00	1718.78	1519.39	1477.69	1672.31
Food	1201.19	961.47	789.45	797.60	928.65
Nonfood	586.91	549.62	496.20	462.06	521.01
Health	80.70	74.38	77.32	81.41	78.44
Education	7.38	5.56	5.18	5.27	5.80
Clothing	98.17	90.19	89.11	90.85	91.90
Grooming	77.81	60.11	49.86	54.15	59.97
Tobacco and cigarettes	9.49	8.25	8.09	8.22	8.48
Transportation	94.59	79.92	79.48	81.86	83.63
Communication	28.67	26.09	23.60	23.49	25.35
Culture	109.86	96.04	91.27	91.47	96.73
Daily per capita caloric intake	2885	2725	2446	2387	2601
Food consumption score	68	61	58	58	61

Source: NRVA 2007/2008. *Note*: Population-weighted means. Real values reflect adjustments for spatial and temporal price differences, covering 13 months of field work. Food expenditure includes the value of home production, gifts, and food aid; see text for details

Afghanistan; the official poverty rate increased from 23.1 % in fall 2007 to 46 % in summer 2008 (MoE Islamic Republic of Afghanistan and the World Bank Economic Policy and Poverty Sector 2010).

To further explore how the food security status of the most vulnerable households was affected by the wheat flour price increases, we controlled for heterogeneous

Table 21.3 Population statistics across the distribution and across the survey year

Quantile	10th	20th	30th	40th	50th	60th	70th	80th	90th	Mean
Full survey year										
Real per capita monthly food consumption	474	572	650	727	810	903	1026	1198	1514	929
Daily per capita caloric intake	1695	1937	2113	2279	2441	2629	2861	3166	3688	2601
Food consumption score	34	42	49	56	61	66	71	78	88	61
Quarter 1										
Real per capita monthly food consumption	552	685	818	937	1058	1201	1371	1585	2020	1201
Daily per capita caloric intake	1740	1992	2236	2452	2679	2938	3240	3628	4262	2885
Food consumption score	40	50	57	64	69	74	79	86	95	68
Quarter 2										
Real per capita monthly food consumption	492	600	684	771	855	954	1083	1264	1566	961
Daily per capita caloric intake	1764	2030	2234	2414	2589	2780	3022	3322	3835	2725
Food consumption score	34	41	47	55	60	66	72	80	92	61
Quarter 3										
Real per capita monthly food consumption	446	528	594	653	720	794	880	1004	1190	789
Daily per capita caloric intake	1663	1899	2062	2217	2351	2499	2678	2937	3311	2446
Food consumption score	32	40	47	53	58	63	69	75	83	58
Quarter 4										
Real per capita monthly food consumption	458	545	614	674	735	806	884	998	1195	798
Daily per capita caloric intake	1610	1873	2023	2144	2279	2426	2617	2861	3263	2387
Food consumption score	33	42	49	55	59	63	67	71	79	58

Source: NRVA 2007/2008. *Note*: Population-weighted estimates at each decile and at the mean, for the survey year and by quarter

price effects on household food security based on a household's level of food security. In Table 21.3, we present the mean of real per capita monthly food consumption, daily per capita caloric intake, and household dietary diversity at each decile (for the survey year and by quarter).

Nearly 30 % of the Afghan households failed to meet the conventional nutritional benchmark of 2100 calories per day, while those at the top of the calorie distribution were well above the threshold. The mean per capita daily caloric intake was approximately 2601.[17] This estimate is in line with worldwide calorie estimates obtained using macroeconomic data; between 2007 and 2009, the average daily calories per capita were 2810 in the world, 2670 in developing countries, and 2380

[17]We assumed the figure has been slightly overestimated due to some food waste and telescoping. For example, Deaton and Kozel (2005) noted that in the case of India, a 7-day food recall period produces higher daily food estimates than a 30-day recall period.

in South Asia (excluding Afghanistan and Bhutan) (FAO 2012).[18] The estimate is also in line with the estimates obtained using nationally representative household data for the region; daily calories per capita was between 2392 and 2593 in Pakistan during the period from 2005 to 2008 (Friedman et al. 2011), and this figure was 2536 in Nepal in 2010/2011 (National Planning Commission and Central Bureau of Statistics 2013).

The mean food consumption score was 61, ranging from 34 at the bottom decile to 88 at the top decile. The WFP uses 48 as a cutoff for an acceptable diet in countries like Afghanistan where most households consume staples and oil every day. Under this categorization, approximately 80 % of the population in Afghanistan has acceptable diets, which is consistent with the food security assessments conducted by the WFP on several other developing countries in recent years. Based on their assessments, the percentages of households with acceptable diets are as follows: Uganda, 78 % in 2013; Rwanda, 79 % in 2012; Malawi, 75 % in 2010/2011; Cambodia, 81 % in 2008; and Pakistan, 82 % in 2008.[19] Recent work has suggested that the cutoff points of the FCS classifications may be too low, for example, when compared with estimates of calorie deficiency (Weismann et al. 2009).

Households at the top of all three distributions experienced the largest declines in food security in percentage terms, while those households at the bottom of the distributions experienced smaller declines in food security. It is important to note that the most food-insecure households were consuming relatively poor diets, and even small declines in quantity and quality of food consumed could have major repercussions on the short- and even long-term nutrition of children in their early development stages.

21.4.4 Price Data

Our analysis focused on the price of domestic wheat flour, the form of wheat most commonly purchased by households. Most wheat is consumed in the form of naan, a type of local unleavened bread that is prepared by households after purchasing either refined wheat flour or whole grain wheat (Chabot and Dorosh 2007). Wheat and other grains constituted 48 % of food expenditure and 70 % of calories consumed.

Table 21.4 displays the mean price of domestic wheat flour by quarter and over the survey year; it also includes other important commodities that we used in the

[18]FAOSTAT provides estimates of dietary energy supply (in kilocalories per person per day), averaged over 3 years and weighted by population. These estimates were calculated using macroeconomic supply data and may be less reliable than estimates derived from household survey data.

[19]Estimates were drawn from WFP reports, available at http://www.wfp.org/food-security/assessment-bank.

Table 21.4 Average prices by quarter and over the survey year

	Quarter 1 (fall)	Quarter 2 (winter)	Quarter 3 (spring)	Quarter 4 (summer)	Survey year
Price of domestic wheat flour	18.09	23.52	34.19	36.51	28.45
Price of vegetable oil	64.81	76.93	88.90	91.70	81.16
Price of domestic rice	33.93	33.99	46.16	55.29	42.77
Price of lamb	182.34	186.20	189.28	180.27	184.44
Price of milk	23.44	25.66	27.23	30.75	26.94
Price of kerosene	43.15	45.77	46.82	55.48	48.12

Source: NRVA 2007/2008. *Note*: Population-weighted means. Prices are in afghani per kilogram or liter

regression analysis to control for simultaneous price increases.[20] The NRVA price data showed patterns which are similar to the FAO GIEWS data in Fig. 21.1, with a marked increase in prices in quarter three of the survey. We chose milk, lamb, rice, and vegetable oil because they (1) represent several key food groups and (2), along with wheat flour, make up a large percentage of monthly household food expenditure; for example, the relatively poor (20th to 50th quantile of the total consumption distribution) spend 80 % of their food expenditure on these five food items. We included kerosene because it is the most commonly used cooking fuel.

A major limitation of this analysis is that we could not disentangle the impacts of the price increases due to three different sets of conditions: the 2007/2008 global food crisis, the 2008 poor harvest, and seasonal variations due to weather and harvest quality. Therefore the results below identify the effect of overall price changes on household food security. If food prices follow a cyclical pattern, dropping in the months after harvest (September–October) and slowly increasing throughout the year as stocks deplete, then we would expect that the price increases were due to the global food crisis and compounded by the cyclical domestic pattern. However, we do not believe that seasonality was a major driver of the price increases. (Recall that Fig. 21.1 displays the retail prices of wheat flour in four major urban centers from 2002 to 2013.) The 2008 price spike was larger than the observed seasonal variation in prices by orders of magnitude. In fact, there is little evidence that monthly prices fluctuate drastically throughout the harvest calendar. Because of transportation costs, it is likelier that prices in remote areas experience greater fluctuations. However, if seasonal wheat flour price patterns were indeed very significant in Afghanistan, we would have observed them in these major urban areas in the years prior to the 2008 spike, but we do not.

The ability to disentangle the causes of the price changes from each other would presumably alter the approach to policy prescription. For example, if the price changes are local rather than global, the policy response would be more

[20]Prices were aggregated to the stratum level in order to mitigate potential measurement error in district-level prices. Strata are based on urban and rural designation within provinces.

targeted, such as releasing grain from reserves to the affected area. If the price changes are global, then the appropriate policy response may be more oriented toward macroeconomic and trade policies. If the price changes are due to anticipated seasonal variations, policies aimed at helping households to smooth consumption, such as improved grain storage, might be desirable. Whereas if the price change is due to a fully unanticipated price shock, which we believe to be largely the case, then the policy response might be more oriented toward short-run safety net programs that focus on nutrition.

21.5 Methodology

We estimated the following reduced-form model of the impact of the wheat flour price increases on measures of household nonfood-based and food-based coping responses:

$$\begin{aligned} \text{ihs}\left(\text{resp}_{\text{h}}\right) =& \beta_0 + \beta_1 \log\left(\text{price wheat flour}_{\text{apq}}\right) + \theta \log\left(\text{prices}_{\text{apq}}\right) \\ &+ \alpha \text{HH}_{\text{h}} + \delta \text{DIST}_{\text{dq}} + \eta \log\left(\text{conflict}_{\text{qp}}\right) + \varPi_{\text{p}} + \varepsilon_{\text{h}} \end{aligned} \tag{21.1}$$

where h denotes household, a denotes area (urban or rural), d denotes district, p denotes province, and q denotes quarter. resp represents one of the household coping responses described above. Prices represent a vector of commodity prices, HH represents a vector of household characteristics, DIST represents a vector of district-level variables, $\varPi$ denotes province dummy variables, and ε is an idiosyncratic error term.

Instead of transforming the dependent variable by taking the logarithm (with or without adding some arbitrary small value to the zero values), we used the inverse hyperbolic sine (IHS) transformation, which reduces the importance of extreme observations (similar to taking logs) but has the additional benefit of being well defined at zero values. The IHS transformation, first proposed by Johnson (1949), was introduced to econometrics by Burbidge et al. (1988).[21] It has been used as an alternative to log transformations for the dependent variable (Burbidge et al. 1988; MacKinnon and Magee 1990) and for explanatory variables (Layton 2001) with variables that can take on zero or negative values. Results can be interpreted in percentage terms, as in log models.

In order to isolate the effect of changes in wheat flour prices, we controlled for simultaneous price increases in other important commodities since (1) household purchasing decisions are based on relative price movements, and (2) omitting such

[21] The IHS function is defined as $\sin h^{-1} = \log\left(x + \left(x^2 + 1\right)^{\frac{1}{2}}\right)$.

variables could bias our coefficient of interest.[22] The price vector includes the prices of milk, lamb, rice (a potential substitute for wheat flour, though not commonly consumed in Afghanistan), vegetable oil, and kerosene for reasons mentioned above.

We included the following household characteristics: dummy for agricultural households (households who report owning or operating agricultural land); log values of durable assets, housing, and livestock; age of household head; dummy for households in which heads are literate; dummy for households in which heads are married; and, separately, the numbers of men, women, and children. We included the agricultural household dummy because these households are able to produce their own food and are thus less reliant on the market. Furthermore, some of these households could benefit from increased wheat flour prices if they are net sellers of wheat. We included the household composition variables to control for differences in consumption requirements between children and adults and for economies of scale in consumption.[23]

The asset values were intended to control for wealth effects and were assumed to be quasi fixed in the short run. Poorer and richer households may have different constraints on their abilities to cope with price increases. For example, richer households have more assets to sell in order to smooth consumption. In a recent contribution, Carter and Lybbert (2012) showed that poorer households are unable to smooth total consumption as well as richer households when responding to weather shocks.[24] Additionally, richer households may have more food-based coping strategies available since they usually consume a more diversified diet of more expensive foods; they then have the option to move toward cheaper foods and food groups as prices increase.

The value of durable goods was estimated based on a detailed inventory of household assets; it accounted for depreciation and the opportunity cost of the funds tied up in the good. The value of housing was estimated using a hedonic model based on characteristics of the structure, as well as the location, to derive an imputed rental value from this.[25] All values are in real afghani.

[22]Given that food prices are often positively correlated with each other and negatively correlated with some of the dependent variables, like food expenditure and caloric intake, omitting the other food price variables would lead to a negative bias on the coefficient of the log of wheat flour price.

[23]An alternative approach to account for such differences employs equivalency scales that take into account nutritional requirements based on age and, sometimes, gender when calculating per capita measures. For an early example, see Buse and Salathe (1978).

[24]It is often assumed the poorer households smooth consumption in the face of shocks; however, using a poverty trap model, Carter and Lybbert (2012) show that below a critical wealth level, poorer households smooth (or protect) assets rather than consumption due to high marginal values of assets and the potential of future-negative shocks.

[25]The estimated housing value is the log of imputed, monthly rental value based on a hedonic model of the housing structure. The log value of assets is a self-assessed valuation based on a list of 13 assets including items such as stoves, refrigerators, radios, sewing machines, and bicycles. For details of the estimation, see Islamic Republic of Afghanistan, Central Statistics Organization (Islamic Republic of Afghanistan et al. 2011).

At the district level, we included dummies for topography—plateau and mountainous areas (plains areas make up the excluded category). Topographical characteristics are related to both agricultural yields and access to markets and thus can affect a household's level of food security. At the province-quarter level, we included a measure of conflict since the level of conflict can be correlated with food prices, as well as household coping responses.[26] We used the ratio of the number of individuals killed or injured in each province during each survey quarter to the province population (in tens of thousands) as our measure of conflict. Finally we also included province dummy variables to control for observable and unobservable time-invariant province-level factors, which could confound the results.

21.5.1 Model Estimation

We used two estimation techniques. For the nonfood-based coping responses, we estimated the parameters above using ordinary least squares (OLS), a commonly used estimator that provides the marginal effect for the mean household. For the food-based coping responses, we estimated the model using both OLS and the unconditional quantile regression (UQR) estimator proposed by Firpo, Fortin, and Lemieux (2009b, hereafter referred to as FFL). The UQR estimator allows the marginal effects to vary based on a household's location on the unconditional distribution of the dependent variable.[27] From a policy perspective, we were interested in heterogeneous price effects on vulnerable households (e.g., those at the bottom of the calorie distribution); we were less interested in how the price effects vary for those who spend a lot or a little on, for example, clothing, and thus we limited the UQR analysis to the food-based coping responses.

For our OLS estimates, we used a standard Huber–White correction to estimate the sampling variance, which allows for the correlation of the residuals within PSUs. The standard errors are also corrected for stratification. For the UQR estimates, we used a PSU-level bootstrap (1000 replications) that accounted for the correlation of the residuals within the PSUs but did not account for the stratification.

[26] In D'Souza and Jolliffe (2013), we examined the relationship between food security and conflict in Afghanistan. We found strong evidence of a negative relationship, as well as evidence that households in provinces with more conflict experience muted declines in food security as a result of wheat flour price increases. We posited that the latter result is because those households were more disconnected from markets (and may have had better coping mechanisms).

[27] By construction, OLS estimates are constant over the entire distribution of the dependent variable and thus cannot elucidate heterogeneous effects for subsets of households. Ex ante, we do not know whether the UQR estimator will provide qualitatively different information than OLS. There is some evidence that the conditional quantile regression estimator provides substantively different estimates. For example, Koenker and Bassett (Koenker and Bassett 1982) show that in the presence of a heteroskedastic error distribution, the quantile estimator will typically differ from the OLS estimator.

The UQR estimator was proposed in 2009 and is becoming a more commonly used tool in policy analysis. The UQR estimator is based on influence functions, which were introduced by Hampel et al. (1988) as a tool in robust estimation techniques.[28] Using notation (largely) defined by FFL, consider some distributional statistics, $\nu(F_y)$, such as the median, inter-quantile range, or any quantile. The influence function, $\mathrm{IF}(Y; \nu, F_y)$, represents the influence of an individual observation on the distributional statistic, $\nu\ (F_y)$, where Y is the dependent variable. A key innovation by FFL is that they added $\nu(F_y)$ to the influence function to center it. This new function is called a recentered influence function (RIF). By design, the expectation of the RIF is the value of the distributional statistic, or more formally, $E(\mathrm{RIF}(Y; \nu, F_y)) = \nu\ (F_y)$.[29]

FFL defined $m_\tau(X) = E(\mathrm{RIF}(Y; \tau, F_y) \mid X)$ as the unconditional quantile regression model.[30] The RIF regression parameter estimates are unconditional quantile marginal effects (UQME) or partial derivatives with respect to the price of wheat flour, as described by the following expression:

$$\frac{\partial Q_{\mathrm{fs}}\ (\tau)}{\partial \mathrm{price\ wheat\ flour}} \tag{21.2}$$

where Q_{fs} is the unconditional quantile function of our food-based coping response measures, and τ represents quantiles of the unconditional distribution. For our analysis, we estimated the marginal effects at all deciles (10th, 20th, ..., 90th) of the food-based coping response distributions while controlling for the covariates in our model specification. The large observed variations in our food-based coping response measures (Table 21.3) suggested that the UQME could differ for households at the bottom and top of the distributions.

An alternative to the UQR is the conditional quantile regression (hereafter CQR) estimator (Koenker and Bassett 1978), which allows behavioral responses to vary across the distribution of the dependent variable after conditioning on the observed covariates (e.g., see Chamberlain 1994). This estimator is based on the conditional population distribution; however, policy questions are typically phrased

[28]Robust statistics are statistics and estimators that are not influenced heavily by deviations from model assumptions nor influenced by single observations. Influence functions provide a formal way of measuring the extent to which a particular estimator is affected by a single observation in the sample.

[29]This is in contrast, for example, to the least absolute deviation (LAD) estimator, whereby the expectation of the LAD is not equal to the median.

[30]FFL provided an estimation method based on transforming the dependent variable into the RIF and subsequently using OLS estimation. FFL have shown that this approach yields a consistent estimator of the average marginal: effect, $E[d\ \Pr[Y > \tau \mid X]/\mathrm{d}X]$, if $\Pr[Y > \tau \mid X = x]$, is linear in x. In order to estimate the standard errors, we followed the methodology proposed by FFL (Firpo et al. 2009b) and used a bootstrap estimator of the sampling variance. For readers who are interested, FFL (Firpo, Fortin, and Lemieux 2009a) derived the asymptotic properties of the estimator and provided the analytical standard errors.

in the context of the unconditional distribution.[31] For example, policymakers may be interested in knowing how price shocks affect the caloric intake of households at the bottom 20th percentile of the calorie distribution of the total population but not the conditional 20th percentile. A key distinction between the two is that the bottom of the unconditioned distribution consists of those who have very low caloric intake, whereas the conditioned distribution need not have low caloric intake (just low caloric intake conditional on their attributes, such as education level). The estimated marginal effects based on the unconditioned distribution can be valuable in targeting vulnerable people for safety net and poverty alleviation programs and in allocating resources in general. The results were robust to using this estimation technique; the observed signs and significance of the results were similar to those of our main results, although with some differences in the magnitudes.

21.6 Results and Discussion

The empirical analysis demonstrated that Afghan households employed both nonfood- and food-based coping strategies in response to the rapid increase in wheat flour prices in 2007/2008. We observed large reductions in real household expenditure across nearly all nonfood categories (Table 21.5). [32] In response to increasing wheat flour prices, households reduced the amount spent on health, clothing, grooming, tobacco and cigarettes, transportation, communication, and cultural activities and practices. (They also reduced food expenditure, which we discuss in more detail below.)

The largest reduction was observed in health expenditure. Such reductions can have serious implications, but we have to be cautious when drawing strong inferences from these results since health expenditures are particularly challenging to interpret. In particular, a decline in health expenditure could indicate either a reduction in the need to treat health problems (i.e., better health) or a failure to take appropriate actions to treat an illness, which would lead presumably to much worse health outcomes. We argue that it is unlikely that a food price shock would be positively correlated with better health outcomes in a food-insecure country like Afghanistan; therefore, we assumed that food prices are either independent of or negatively correlated with health outcomes. In such cases, the observed reduction in health expenditures would indeed represent a coping behavior, whereby health needs are sacrificed to mitigate the shock to food consumption.

In the development literature, there is evidence that household behavior differs with respect to adult goods and child goods (Deaton and Paxson 1998). Expenditure

[31] As an exception to this assertion, Buchinsky (1994) provides an example in which the question posed is best answered by the CQR estimator and not something akin to the UQR. He examined the distribution of wages in the USA and, using the CQR estimator, provides insight into how wage inequality within groups (i.e., conditional on being in a specific group) changes over time.

[32] The tables display the coefficients of interest. Full results are available upon request.

Table 21.5 Effects of wheat flour price increases on real per capita expenditure

Nonfood	Health	Education	Clothing	Grooming	Cigarette and tobacco	Transportation[a]	Communication	Culture	Food
−0.121***	−0.432***	−0.037	−0.084*	−0.330***	−0.177*	0.310*	−0.255**	−0.262*	−0.423***
[0.044]	[0.085]	[0.089]	[0.051]	[0.053]	[0.101]	[0.168]	[0.128]	[0.146]	[0.036]

Note: Coefficients and standard errors are from separate, population-weighted regressions. The dependent variable is real per capita expenditure for each group (listed at the top of the columns), transformed by the inverse hyperbolic sine (IHS) function. Control variables are listed in the text

*, **, and *** denote significance at 10 %, 5 %, and 1 %, respectively; [a]In the transportation regression, the log of the price of gasoline is included as an additional control variable. Total observations: 20,483. Standard errors are clustered bootstrap estimates

Table 21.6 Effects of wheat flour price increases on real per capita expenditure

Adult clothing	Children's clothing
−0.113**	0.092
[0.051]	[0.074]

Note: Coefficients and standard errors are from separate, population-weighted regressions. The dependent variable is real per capita expenditure for each group (listed at the top of the columns), transformed by the inverse hyperbolic sine (IHS) function. Control variables are listed in the text. Total observations: 20,483. Standard errors are clustered bootstrap estimates

*, **, and *** denote significance at 10 %, 5 %, and 1 %, respectively

Table 21.7 Effects of wheat flour price increases on other nonfood-based coping responses

Sold livestock	Member migrated	Child in school	Purchased food on credit
−0.014	0.007	−0.0028	0.084**
[0.010]	[0.022]	[0.018]	[0.043]

Note: Coefficients and standard errors are from separate, population-weighted regressions. The dependent variable is indicator variable for action listed at the top of the column except for the last column; purchased food on credit is a categorical variable ranging from 1 (never) to 4 (always). Control variables are listed in the text. Total observations in column 1 and 2: 20,483; total observations in column 3: 15,924 (in the child-level regression). Standard errors are clustered bootstrap estimates

*, **, and *** denote significance at 10 %, 5 %, and 1 %, respectively

on grooming and on tobacco and cigarettes is typically categorized as adult goods, in addition to alcohol (not solicited in the NRVA survey) and adult clothing. The NRVA data allowed us to distinguish between clothing and shoes for adult and child. As shown in Table 21.6, we observed that households reduced the amount spent on adult clothing but did not make adjustments to child clothing expenditure. Furthermore, we did not find any effect of the price increases on education, which is a children's good. We interpret these results as evidence of Afghan households prioritizing—to a certain extent—child goods over adult goods in their nonfood-based coping responses.

We did not find evidence of the use of other nonfood-based coping responses, with the exception of an increase in frequency at which households purchase food on credit (Table 21.7).[33] We failed to find evidence of changes in the sale of livestock, in the migration of household members, and in school enrollment. Selling productive assets and migrating are extreme responses and could be potentially irreversible;

[33]The variable for purchasing food on credit is categorical, with values ranging from one to four. The displayed coefficient comes from an OLS model; however, the results are qualitatively similar to the coefficient from an ordered probit model.

therefore, it is not surprising that households chose other coping strategies in lieu of these. As with educational expenses, households might have chosen to protect the investment in children by keeping them enrolled in school. Given the substantial decline in purchasing power, it is not surprising that households purchased food on credit more frequently; incurring even small amounts of debt could encumber a household and perpetuate the cycle of poverty.

Our nonfood-based coping response findings are consistent with the qualitative evidence presented by Lautze et al. (2002), who examined the coping strategies employed during times of drought in Afghanistan using focus groups across the country. In addition to reducing the quality, quantity, and frequency of their meals, Afghan households reported taking on debt and decreasing cultural celebration expenses related to Qurbani Eid. They also found that households sold off assets, increased migration, and increased their reliance on remittances.

For the food-based responses, we estimated the price effects for the mean household using OLS and for households at each decile of the unconditional distribution of the dependent variable using the UQR estimator (Table 21.7). For the mean Afghan household, we observed a large decline in real per capita food consumption and relatively smaller declines in calories and dietary diversity. We interpreted these results as a trade-off between quality and quantity that the household made in order to maintain energy levels in the face of declining purchasing power. More specifically, the mean Afghan household adjusted the composition of its diet in order to buffer the price shock to a certain extent (i.e., calories and diversity decline less than food expenditure).

Additionally, in the regressions above, we allowed the price effects to vary based on whether the household owned or operated agricultural land (the results are available in D'Souza and Jolliffe 2014). During periods of high food prices, these households may not be hurt as much as other households because they are able to produce their own food and are less dependent on the market. Furthermore, if they produce more food than they consume (i.e., net sellers), they can sell the food on the market and profit from the high prices. The NRVA data did not allow us to identify net sellers of wheat, and so we used a dummy for agricultural households. We did not find any strong systematic patterns that were consistent with the literature (i.e., agricultural households are better able to cope with the price increases). Nevertheless, the severe drought of 2008 would have limited the number of net sellers of wheat in Afghanistan at that time. The drought was the worst in the ten preceding years, with losses reported on both rainfed and irrigated wheat crops (Foreign Agricultural Service 2008).

The UQR estimates showed that increases in the wheat flour prices were associated with statistically significant declines in these food-based coping responses across much of the respective unconditional distributions. We observed the largest percentage decline in food consumption and calories for the Afghan households at the top of the respective distributions, with smaller declines observed as one moves lower on the distributions.[34] At a very basic level, these households had more to give as they are well above food poverty thresholds and daily energy (calorie) requirements; they also hosted more guests and ate more away from home, on average, than poorer households.[35]

Households at the first decile of caloric intake were living below the threshold of energy requirements (with average daily per capita caloric intake of 1670) and presumably were unable to cut back on calories without suffering serious nutritional consequences. Accordingly we found no evidence of a decline in their caloric intake. Even those at the second decile experienced negligible changes, equivalent to less than a third of a standard naan (one piece of Afghan bread). Sulaiman et al. (2009) found that Bangladeshi households at the third and fourth income quintiles experienced more wasting than the poorest households in the case of food price increases. Furthermore, there has been some empirical evidence that by moving to cheaper foods and employing nonfood-based coping strategies, households may be able to maintain energy levels despite food price increases. For example, Jensen and Miller (2008) found no reduction in calories among poor households in China's Hunan province and a very small reduction in calories among poor households in Gansu province (indistinguishable from typical seasonal declines) when food prices increased in 2006. They also found evidence of consumers moving away from more expensive foods and a slight reduction in nonfood expenditure.

The strong pattern of the price effects on food consumption and calories stands in contrast to the standard result in the literature that poorer households have larger food price elasticities.[36] The standard result hinges on the fact that richer households devote a much smaller share of their budgets to food and thus are not as affected by food price increases as poorer households. In Afghanistan, however, food (in particular, wheat) makes up a large portion of the budget for rich and poor households alike. Over 80 % of the population spends more than half of their total budget on food. Those in the bottom quintile of the income distribution spend approximately 66 % of their budget on food (44 % on wheat flour); even those in the top quintile spend approximately 49 % of their budget on food (20 % on

[34]We note here the standard caution that the regression coefficients represent estimated effects from small, marginal price changes. This caution against using estimated marginal effects as a basis for simulating large, non-marginal price changes is particularly warranted in the case of quantile estimators where different estimated effects across the distribution of the dependent variable imply a changing shape of this distribution due to price changes. Variation in the estimated marginal effects at different points on the distribution can readily imply re-rankings of observations (in terms of the dependent variable) with large enough simulated changes. But this exercise would be nonsensical as one would expect that as the shape of the distribution changes, so too would each of the estimated marginal effects.

[35]For example, households in the top quintile of the calorie distribution spend nearly double on food away from home than households in the bottom quintile, and they provide more meals (approximately two per week) to guests.

[36]The elasticities are not completely comparable since we looked at calorie-price elasticities based on where the household lies on the calorie distribution, and in the literature the analyses often focus on demand for food based on a household's income quintile.

Table 21.8 Effects of wheat flour price increases on food security across the distribution

Quantiles	10th	20th	30th	40th	50th
Real per capita monthly food consumption	−0.131** [0.0521]	−0.199*** [0.0448]	−0.268*** [0.0440]	−0.338*** [0.0446]	−0.431*** [0.0475]
Daily per capita calorie intake	−0.00531 [0.0439]	−0.0724** [0.0296]	−0.120*** [0.0277]	−0.156*** [0.0258]	−0.192*** [0.0268]
Food consumption score	−0.239*** [0.0575]	−0.242*** [0.0520]	−0.241*** [0.0479]	−0.181*** [0.0369]	−0.168*** [0.0302]
Quantiles	60th	70th	80th	90th	OLS
Real per capita monthly food consumption	−0.505*** [0.0486]	−0.590*** [0.0546]	−0.706*** [0.0660]	−0.721*** [0.0759]	−0.423*** [0.036]
Daily per capita calorie intake	−0.225*** [0.0287]	−0.266*** [0.0335]	−0.313*** [0.0372]	−0.377*** [0.0477]	−0.187** [0.0243]
Food consumption score	−0.152*** [0.0309]	−0.151*** [0.0300]	−0.188*** [0.0334]	−0.185*** [0.0329]	−0.183** [0.0270]

Note: Coefficients and standard errors for the log of wheat flour prices are from separate, population-weighted regressions. The dependent variable is transformed using the inverse hyperbolic sine function and is listed in the first column. Control variables are listed in the text. Total observations: 20,483. UQR standard errors are clustered bootstrap estimates. OLS standard errors are corrected for clustering and stratification

*, **, and *** denote significance at 10 %, 5 %, and 1 %, respectively

wheat flour). Given the importance of food in the budget of Afghan households, it is plausible that even those households at the top of the distributions could have been affected significantly by the wheat flour price increases.

The estimates from the FCS regressions revealed that Afghan households had to make large concessions in dietary quality as a result of the food price increases (Table 21.8). In the case of Haiti, Brinkman et al. (2010) found similar declines in the FCS when rice prices increased. These findings indicated that households changed the composition of their diets, perhaps by cutting back on more expensive, nutrient-rich foods and moving toward cheaper foods. Since the UQR coefficients are related to a specific quantile of a specific distribution, we could not establish a link between the results for the three food-based coping responses. That is, households in a certain quantile on one distribution do not necessarily fall in the same quantile on another distribution; therefore, each set of coefficients must be interpreted separately. While we acknowledge that households may be giving up quality for quantity, we could not provide direct evidence using the UQR.

Our overall findings on food security are consistent with the literature on the impact of economic shocks on nutritional outcomes. For example, Klotz et al. (2008) argued that during times of economic crisis and when households cannot increase the amount that they spend on food, they are forced to cut back on expensive, micronutrient-rich foods to maintain their consumption of core staples. Therefore, economic shocks will lead to micronutrient deficiencies before weight loss. Jensen and Miller (2008) similarly found that in the face of food price inflation, poor urban households in China substitute more expensive foods with cheaper foods. Diagana et al. (1999) also found decreases in the level of dietary diversity and changes in food consumption patterns after the 1994 devaluation of the CFA franc using data from West Africa.

Our results also highlight the importance of moving beyond price effects on mean households when conducting policy analysis; in some instances, we observed stark differences between the coping responses of the average household and households at other points on the distributions. Figure 21.3a and b depict the UQR and OLS point estimates and the 95 % confidence intervals for the food consumption and calorie regressions, respectively.

There are substantial differences between the UQR and OLS estimates for the food consumption and calorie regressions. OLS overestimated the responses of those at the lower portion of the distributions and underestimated the responses of those at the upper portion of the distributions. This could have policy implications.

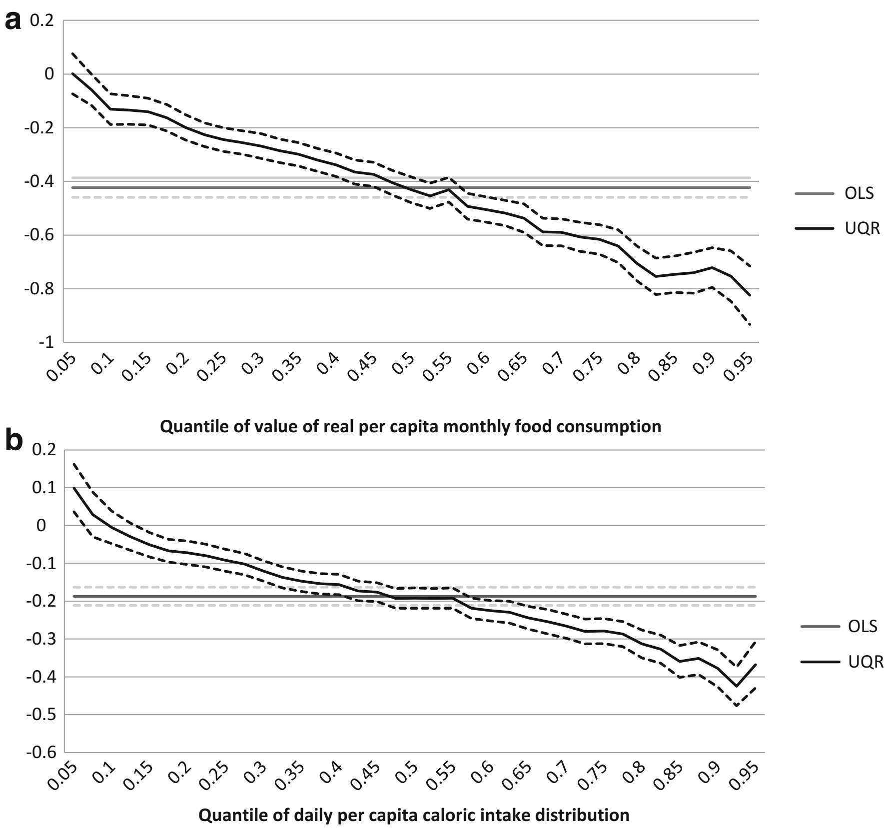

Fig. 21.3 (**a**) Food consumption-price effects (with 95 % confidence intervals). (**b**) Calorie-price effects (with 95 % confidence intervals)

For example, if policymakers consider solely the OLS results for calories and then assume that all households, including the most vulnerable, reduce their caloric intake in response to the price increases, this could lead to blunt policy responses which focus on the provision of staple foods alone. These sorts of policies would not only exacerbate the price shock by shifting up the demand for staple food (through government purchases), but they are likely to be a relatively more expensive safety net option (given that price increase of the staple). More importantly, the UQR results showed that the most vulnerable households do not cut back on calories, and thus other policies may be more beneficial. It is likely that some of these households were forced to make other concessions, such as moving to lower quality and/or less nutritious foods; in this case, interventions like nutrient supplementation programs or the fortification of staple foods could address better the needs of those households.

21.6.1 Supplemental Results

To explore further the impact of the price increases on food security, we looked at several supplemental indicators of diet quality to examine the potential nutritional consequences of dietary changes. We examined three essential micronutrients (retinol, beta-carotene, iron) and the three macronutrients (protein, carbohydrates, fat). Retinol and beta-carotene are forms of vitamin A, an important nutrient for vision and immune system functions. Iron is critical for growth and development, immune system functions, and overall metabolism. Both vitamin A and iron deficiencies are ubiquitous in developing countries and have been recognized as major public health challenges (Dufour and Borrel 2007; Fanzo and Pronyk 2010; Ramakrishnan 2002). The three macronutrients provide energy (or calories) to the body and are essential—in large quantities—for survival. Similar to the food-based coping response regressions above, we used the inverse hyperbolic sine function to transform these dependent variables and used the UQR estimator to estimate the price effects based on a household's position on the unconditional distribution of the respective nutrient intake variable.

We observed declines in nutrient intakes as a result of the wheat flour price increases (Table 21.9). The results differed by the type of nutrient as well as the position of a household on the distribution of nutrient intake. We found declines in the intake of iron, retinol, and beta-carotene for most households, with the lowest deciles of the distributions being an exception (and for beta-carotene, those in the top deciles as well). The general declines are consistent with the findings of Ecker and Qaim (2011), who found negative staple food price elasticities (at population means) for iron and vitamin A (and protein) in Malawi.

In terms of macronutrients, we found a decline in the intake of protein, fat, and carbohydrates; the intake of the first two macronutrients showed larger declines, as may have been expected since protein and fat are more expensive sources of calories than carbohydrates. We found that households at the lower end (e.g., first and second deciles) of these distributions did not experience statistically significant declines.

Table 21.9 Effects of wheat flour price increases on micronutrient and macronutrient intakes

Quantile	10th	20th	30th	40th	50th	60th	70th	80th	90th
Iron	0.055	−0.00752	−0.0633*	−0.0891***	−0.123***	−0.140***	−0.157***	−0.181***	−0.189***
	[0.0554]	[0.0388]	[0.0342]	[0.0315]	[0.0310]	[0.0318]	[0.0352]	[0.0399]	[0.0462]
Retinol	−0.000***	−1.427***	−1.030***	−0.679***	−0.712***	−0.640***	−0.553***	−0.420***	−0.431***
	[0]	[0.405]	[0.297]	[0.180]	[0.142]	[0.116]	[0.108]	[0.105]	[0.100]
Beta-carotene	−0.127	−0.0925	−0.123	−0.301**	−0.337***	−0.349***	−0.294***	−0.188*	−0.0933
	[0.151]	[0.156]	[0.146]	[0.121]	[0.102]	[0.101]	[0.0933]	[0.101]	[0.112]
Carbohydrate	0.00623	−0.038	−0.0875***	−0.134***	−0.162***	−0.202***	−0.222***	−0.250***	−0.356***
	[0.0478]	[0.0340]	[0.0284]	[0.0290]	[0.0299]	[0.0304]	[0.0341]	[0.0378]	[0.0497]
Fat	−0.00129	−0.145***	−0.196***	−0.258***	−0.310***	−0.350***	−0.389***	−0.455***	−0.457***
	[0.0606]	[0.0438]	[0.0375]	[0.0354]	[0.0381]	[0.0368]	[0.0386]	[0.0500]	[0.0519]
Protein	−0.00297	−0.0572*	−0.122***	−0.179***	−0.237***	−0.289***	−0.413***	−0.685***	−2.533***
	[0.0470]	[0.0338]	[0.0316]	[0.0317]	[0.0323]	[0.0362]	[0.0467]	[0.0920]	[0.736]
Animal-source	−1.275***	−0.618***	−0.606***	−0.571***	−0.493***	−0.443***	−0.466***	−0.404***	−0.587***
protein	[0.382]	[0.151]	[0.117]	[0.100]	[0.0914]	[0.0800]	[0.0745]	[0.0733]	[0.0839]
Nonanimal-source	0.0357	−0.0564*	−0.106***	−0.150***	−0.221***	−0.269***	−0.369***	−0.579***	−2.813***
protein	[0.0507]	[0.0315]	[0.0302]	[0.0305]	[0.0318]	[0.0383]	[0.0494]	[0.0959]	[0.878]

Note: Coefficients and standard errors are from separate, population-weighted regressions. The dependent variable is per capita nutrient intake transformed by the inverse hyperbolic sine (IHS) function. Control variables are listed in the text. Total observations: 20,483. Standard errors are clustered bootstrap estimates
*, **, and *** denote significance at 10 %, 5 %, and 1 %, respectively

We further separated protein-based food into two categories: animal-source foods and nonanimal-source foods. Higher animal-source and nongrain food expenditures have been linked to lower levels of malnutrition as measured by child stunting (Sari et al. 2010). We found that the expenditure on animal-source protein declined much more than nonanimal-source protein when food prices increase; the former is a more expensive source of calories than the latter. The largest change overall was the decline in protein from animal sources for those consuming at the lowest decile. Across each of the deciles, the negative elasticity of protein from animal sources was the largest change of the macronutrients. These findings are consistent with the fact that as purchasing power declines, households move away from more expensive and often nutritious calories, such as meat, to cheaper less nutritious ones, such as pulses and beans. The findings are also consistent with previous literature on economic shocks. Martin-Prevel et al. (2000) and Block et al. (2004) found reductions in maternal and child nutritional status following a currency devaluation and a financial crisis.

21.7 Conclusion

Unique household and price data collected before and during the 2007/2008 food price crisis provided a rare opportunity to examine empirically nonfood-based and food-based coping strategies used by households in Afghanistan in response to sharp increases in the price of wheat flour, their dietary staple. In a country where decades of conflict, political instability, and recurring drought have led to a precarious state of food insecurity and poverty, understanding how households cope with price increases and other economic shocks can provide vital information to policymakers and aid organizations tasked with creating and implementing programs and policies to address acute and chronic food insecurity and poverty in Afghanistan.

In response to wheat flour price increases, we found that Afghan households reduced food expenditure and also expenditure on health, grooming, communication, transportation, cigarettes and tobacco, and culture. The reductions in health expenditures are of particular concern, especially in a country that ranks at the bottom of many development, health, and nutritional rankings. Such coping responses could have long-term consequences if they represent reductions in important medical care or health investments.

We did not find changes in educational expenses, school enrollment, or child clothing, which can be categorized as child goods. The reductions in expenditures on grooming, adult clothing, and cigarettes and tobacco suggest Afghan households were more willing to reduce spending on adult goods than child goods. While we did not observe any increase in the sale of productive assets (livestock) or in migration, we did find an increase in the frequency at which households used credit to purchase food.

The food price increases also led Afghan households to employ several food-based coping strategies. Households reduced the real per capita monthly value of food consumed and as a result experienced reductions in daily per capita caloric intake and household dietary diversity. Rather than reducing calories by the same amount as the reductions in the value of food consumed, households adjusted the types of foods they ate; most likely, they switched to lower quality, cheaper foods, or food groups.

We further analyzed the food-based coping responses by examining the differences in the behavioral response of a household based on its location on the distribution of the respective food-based coping response indicators. Those wishing to target policies and programs at vulnerable, food-insecure households may be interested in knowing the unique set of trade-offs that these households face. Households at the bottom of the caloric intake distribution made very small to no reductions in caloric intake. Households living near caloric-subsistence levels are vulnerable to many adverse health effects and need to find ways to absorb the price shock without further reducing calories. These vulnerable households may have limited options in buffering food price shocks; while we know that food purchases make up the vast majority of their total consumption, they cannot easily scale back on calories. Whereas we found that households at the top of the distribution did experience significant declines in caloric intake. Similarly, households at the top of the food consumption distribution experienced larger declines than those at the bottom of the distribution, though unlike in the calorie regressions, even those at bottom experienced significant declines. Such differences in behavioral responses show that a quantile estimator (or any estimator that allows marginal effects to vary across the distribution) can reveal important information, particularly when examining welfare-related outcomes.

We also found evidence of declines in dietary diversity across the entire distribution of households in Afghanistan, underscoring the vulnerability of Afghan households to food price increases. Long-run policy solutions recognize that vulnerable households are likely to be disproportionately hurt by negative shocks. Antipoverty programs aimed at increasing the income of the poor and improving access to infrastructure and education could better protect people from price shocks by providing them with better coping strategies (e.g., drawing down savings rather than decreasing health expenditure).

A long-run approach alone can, however, leave the population vulnerable to shocks in the short and medium run. Short-run interventions can play a potentially important role in protecting the population from long-run adverse effects of food price shocks. As an example, our analysis demonstrated that dietary quality (dietary diversity, as well as nutrient intake) declined significantly during a period of high food prices. Examples of interventions that focus on diet quality include micronutrient supplementation programs (such as “sprinkles”), expansion of the fortified school biscuit program, wheat flour fortification (e.g., with iron, folic acid, or vitamin A), and biofortification of staple crops. Such interventions play a relatively small role in food assistance programs. For example, between 2005 and 2009, more than 1.12 million metric tons of food aid was delivered to Afghanistan to provide emergency food relief and nutritional support to vulnerable and acutely food-insecure households; more than three-fourths of this aid was comprised of wheat products. It is important to note that our findings do not argue against the provision of calories through the release of staple crop reserves. Even though we found that those whose calorie consumption is at the margin of basic caloric needs are not reducing their caloric intake during an adverse price shock, this does not mean that the provision of some form of calories will not be of help to them. The receipt of a staple crop could very well be a useful transfer, allowing the household to supplement the staple crop with a more diverse diet or purchase necessary nonfood items. The standard response to food crises—increasing the distribution of grains—is useful because it essentially increases the ability of a household to consume a more diverse diet. The key findings in this analysis, though, put more emphasis on the importance of enhancing the current standard policy response with interventions aimed directly at addressing dietary diversity through micronutrient interventions, such as fortification of grains or nutrient supplementation.

Another policy implication related to the monitoring of a population's vulnerability to food insecurity. In their guidelines for assessing household-level food security, the Food and Agriculture Organization of the United Nations and the World Food Programme (2009) suggested the construction of a food consumption score, food expenditure estimates, and caloric intake. The guidelines have been written to provide assistance to on-the-ground teams which assess whether action needs to be taken to address the potential problems of food insecurity. The guidelines are intended to be practical responses to data-poor environments and suggest that information on any of these indicators could be informative, but our findings are less optimistic about the informativeness of calories as a proxy for food security in the short run. Our findings indicated that calories are relatively insensitive (at least in the short run) to adverse shocks, while dietary diversity is more sensitive to shocks. This is consistent with the findings of Ruel (2003), who found that dietary changes can be detected before changes in micronutrient status. The key point is that policies designed to be triggered by a decline in caloric intake to below the subsistence level will fail to detect the onset of food insecurity in a timely way.

Finally our findings shed some light on the costs and benefits of collecting data on diversity and calories. Household survey consumption modules often include questions about the quantity of food consumed and food expenditure, but questions about the frequency of food consumption are seldom asked. Given its low cost, it may be beneficial to consider augmenting household surveys by adding such questions, particularly for populations that are vulnerable to food insecurity. Measures of dietary diversity are a useful tool when detailed food journals or anthropometric data are not available. A common view is that there is a trade-off between different measures, such as the food consumption score and calorie measures. Calorie data is time consuming to collect, but it is presumably a better indicator of food security, while dietary diversity data is easier to collect, but it is a cruder, less informative measure. Alexander and Thomson (1992) discussed the importance of collecting frequency data in addition to quantity intake data. They demonstrated that both the quantity and frequency of food intake are important determinants of diet-induced diseases, and they argued that looking solely at quantity data could be misleading. Our findings suggest that using dietary diversity indicators may be the best approach to measuring the onset of food insecurity. This view is supported by recent literature comparing various measures of food security (Headey and Ecker 2013; Tiwari et al. 2013).

Acknowledgments The authors are grateful to the Central Statistics Organization, Government of Afghanistan (GoA), for granting access to the data for poverty research. Findings from this analysis provided background information for the World Bank's poverty assessment for Afghanistan and have informed the GoA Ministry of Economy. The authors wish to thank for comments of Ismail Rahimi and participants at the ZEF-IFPRI Workshop on Food Price Volatility and Food Security. D'Souza is an Associate Professor at the School of Public Affairs, Baruch College, CUNY; Jolliffe is a Senior Economist at the World Bank and also holds affiliations with the Institute for the Study of Labor (IZA) in Bonn and with the National Poverty Center (NPC) at the Ford School of Public Policy, University of Michigan. The views expressed here are those of the authors and may not be attributed to the World Bank, IZA, or NPC.

Appendix

Table 21.10 Key indicators across quarters

	Quarter 1 (fall)	Quarter 2 (winter)	Quarter 3 (spring)	Quarter 4 (summer)	All
Demographic Indicators					
Average household size*	8.7	9.0	8.4	8.5	8.6
Average age (years)	20.6	20.4	20.7	20.5	20.6
Household members %, age <15)	47.9	48.7	48.4	48.7	48.5
Age dependency ratio	131.6	134.2	133.6	134.0	133.4
Education and health indictors					
Full Immunization (%, age 12–23 months)*	33.0	41.1	34.8	37.6	36.7
Literate household head (%)*	34.4	28.8	28.4	29.5	30.1
Ever attended school (%, age >18)*	21.7	21.3	18.9	21.6	20.9
Education level of persons (age >18)	2.0	1.9	1.6	1.9	1.9
Access to services and infrastructure indicators					
Sanitary toilet (% households)	5.9	5.6	4.5	4.0	4.9
Electricity (% households)	40.9	42.2	41.5	39.8	41.1

Source: NRVA 2007/2008. *Note*: Population-weighted means
* denotes estimates that are statistically different at 10 % across quarters in some cases

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Hedging Seasonal Food Price Risks: The Impact of Cereal Banking in the Gambia 22

Raymond Jatta

22.1 Introduction

In rural communities of the Gambia, as in the case of most other arid and semiarid countries in the world, cereal banking is a common practice to store food at harvest for use during lean periods. It is a community-based strategy of making food available throughout the year and managing seasonal food price dispersions by maintaining physical food reserves (Beer 1990). It aims at managing price and climate risks.

Rainfall variability and food price volatility are some of the most important risk factors that affect lives and livelihoods of poor rural households in import-dependent countries such as the Gambia (Vicarelli 2011, p. 2; Wright and Cafiero 2009). This is due in part to their primary sector-based economy (which is sensitive to climate conditions), their reliance on food imports, and their low levels of human development and food accounting for a major part of their income and expenditure (Kalkuhl et al. 2013; Wheeler and von Braun 2013; FAO 2011). These factors account for high human costs resulting from climate and market shocks (FAO 2011; von Braun and Tadesse 2012; Ivanic and Martin 2008).

In this chapter, we assess how cereal banking can be used as a viable option in rural communities to enhance food and livelihood security in the face of climate and price risks. In spite of cereal banking's popularity in most of the arid and

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M. Kalkuhl et al. (eds.), *Food Price Volatility and Its Implications for Food Security and Policy*, DOI 10.1007/978-3-319-28201-5_22

semiarid rural communities (Basu and Wong 2012; Bhattamishra 2012), the practice has received little empirical scientific research.

22.2 Context

Our study was conducted in 134 rural communities, in a total of 13 districts from three of six rural regions in the Gambia. 78 % of the active population in the Gambia is engaged in rain-fed subsistence farming as a source of income and food. Households in rural areas are generally larger (>12 members) and poorer, with 48 % of the households below the national poverty line of $1.08 a day (GoG 2010). The traditional land tenure system allows for small land holdings inequitably distributed among men and women (von Braun et al. 1989; Carney 1992). In addition to other socioeconomic factors—such as urbanization, population growth, inadequate input supply and the use of crude technology—rainfall variability has an important multiplier effect on the ability of households to feed themselves. The Gambia's climate is Sahelian semiarid. Its location has been described as a hotspot for climate change and food insecurity (Ericksen et al. 2011). The climate consists of two seasons: a 4-month rainy season (June–September) and an 8-month dry season. Because the rainy season is short, only a single cropping season is feasible for rain-fed agriculture[1] (Ceesay 2004). Only about 50 % of the country's food needs is produced locally (WFP 2011). The Gambia is thus regarded as a food-deficit, import-dependent country. Inter-annual variations in food production generally follow rainfall trends and variability.

Figure 22.1 shows an almost perfect positive correlation between rainfall variability and cereal production variability. Variability in Fig. 22.1 is a measure of dispersion of each annual rainfall or production figure from their mean between 1991 and 2012, normalized by their standard deviation.

Figure 22.2 shows the gap between domestic consumption and production. Rainfall variability has the potential to reduce domestic production. When coupled with a global food crisis and a price hike, it could cause food prices to rise drastically, eroding purchasing powers and resulting in poverty and malnutrition among many Gambians (Kalkuhl et al. 2013). Given the country's dependence on food imports[2] (60 % estimated by Tadesse et al. 2013), any changes in global food availability and food prices will definitely affect foreign exchange rates, causing inflationary pressures on food and non-food imports.

Food production, affordability, and consumption in rural areas of the Gambia follow the agricultural cycle (Barrett 1996), as in most developing countries. During harvest season, food is in abundance, and most households become net suppliers of food. In the Gambia, the harvest season spans from October to February. Food supplies tend to move from rural to urban areas because of higher prices (a

[1] Irrigated area is less than 6 % of arable land.

[2] WFP (2011) estimates 81 % dependence on rice imports, the country's staple food.

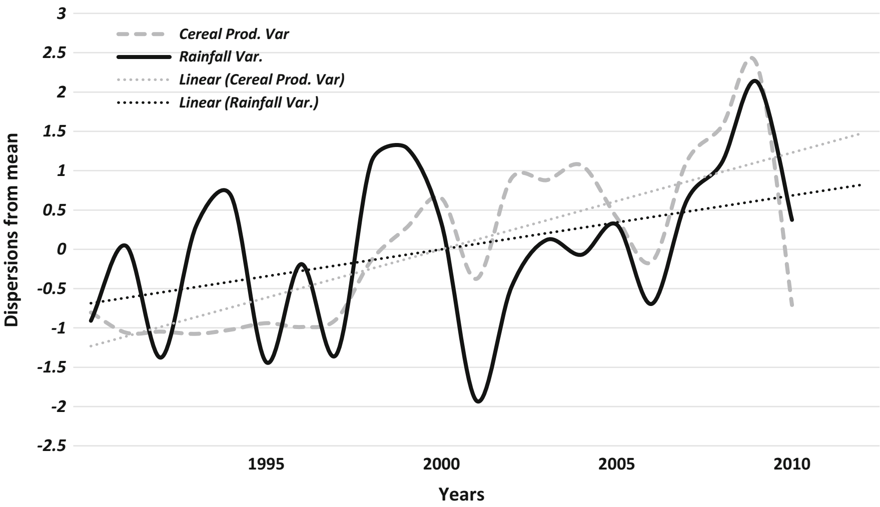

Fig. 22.1 Crop production and rainfall variability, 1991–2012. *Source*: Department of Water Resources, Gambia

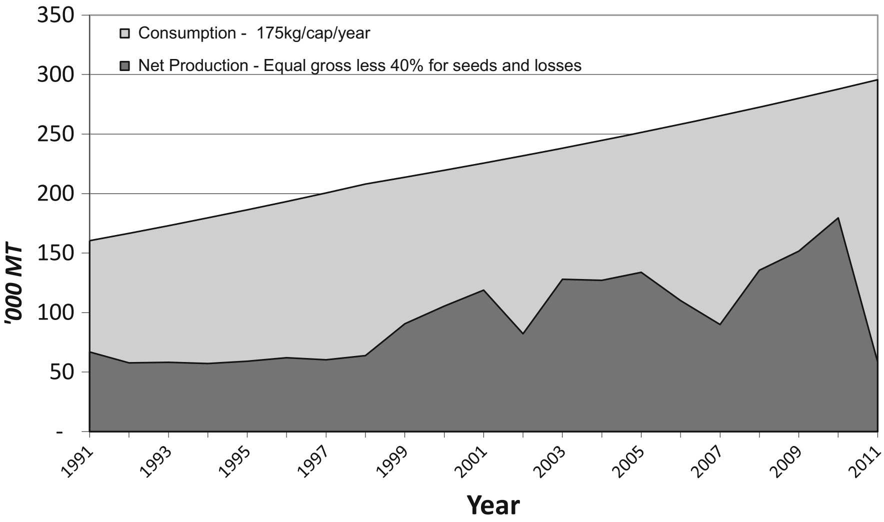

Fig. 22.2 Consumption requirement vs. net cereal production 1991–2011. *Source*: World Food Programme—WFP (2011). Note: consumption requirement in the Gambia in 1000 metric tons to meet a cereal demand of 175 kg/cap/year

consequence of higher demand) in the urban areas (Barrett 1996). However, food is usually in short supply when approaching the rainy season (FAO 2011). Rural households and communities become net buyers and often have to rely on imported food from the urban areas. The reversal of food flow begins driving upwards food prices in rural areas. Production constraints, exacerbated by the absence of large storage schemes and credit constraints, tend to worsen the price changes and the spatial and temporal food availability (Barrett 1996). The transition in terms of the duration of the food gap is influenced by rainfall patterns, among other things. In years with low rainfall, inter-seasonal food price dispersion can be as high as up to 400 % (von Braun et al. 1999). This dynamic affects rural households and communities more—eroding incomes and causing seasonal food and nutrition insecurity (WFP 2011). As a result, the problem of food insecurity is more seasonal than chronic in rural areas of the Gambia. Every year, poor households in the rural areas face the "hungry season," a period of 3–4 months between July and September, when household food stocks are low or depleted (FAO 2011). The Comprehensive Food security and Vulnerability Assessment Report (WFP 2011) observed that in the months of August and September, about 80 % of the rural households reported food-insecure conditions, while only 10 % reported being food insecure between December and April. Similar studies on seasonal food security programs in East Indonesia and Bangladesh (Basu and Wong 2012; Khandker 2009 respectively) observed similar seasonal food insecurity dynamics.

22.3 Methodology

Our methodology is based on a large scale randomized control trial (RCT) implemented in the Gambia called the Community Driven Development Project (CDDP). The project, funded by the World Bank, was implemented in the Gambia from 2008 to 2011. Using a poverty index as a basis for stratification, 930 out of about 1800 villages were eligible, and of the 930 eligible villages, 495 were randomly chosen for the CDDP intervention (Arcand et al. 2010). 35 of the 495 villages chose cereal banking from a wide range of possible projects based on the needs and aspirations of their communities.[3]

We note that while selection for CDDP intervention was randomized, the choice of subprojects such as cereal banking was not. It was likely influenced by endogenous village characteristics. Evaluating the impact of such subprojects requires the use of quasi-experiments (Abebaw and Haile 2013).

Subsequently, we have to investigate the determinants making these villages choose cereal banking for their subproject. These factors must be controlled to minimize selection bias and fulfil the Conditional Independence Assumption (CIA) (Heckman et al. 1997; Angrist and Pischke 2008).

[3]Participatory project identification methods were used; villagers chose the subproject at village meetings.

22.3.1 Propensity-Score Matching

In propensity-score matching (PSM), researchers try to balance groups by matching treatment and control units based on the characteristics that affected their probability of receiving treatment—which, in this case, is cereal banking (Heckman et al. 1997; Caliendo and Kopeinig 2008). PSM ensures that at baseline and on average, groups are identical in terms of observed characteristics (Heckman et al. 1997; Caliendo and Kopeinig 2008). The method requires finding a control group which bears similar characteristics as the treatment group in all respects; however, the control group does not receive treatment. If a treated group and a potential control group have matching propensity scores, then the difference between outcomes of the two groups is an unbiased estimator of the treatment effect (Heckman et al. 1997; Ravallion 2007; Abebaw and Haile 2013). However, this assumption becomes invalid if there are important unobservable factors that affect treatment and outcomes (Caliendo and Kopeinig 2008). The method can be improved by using fixed effects which captures time-invariant unobserved heterogeneities (Olken 2012).

We estimate the propensity of a community participating in a cereal banking scheme using a nonparametric logit model:

$$P\,(\mathrm{CB}) = \beta \mathrm{Vc}(i) + \varepsilon(i), \tag{22.1}$$

where $P(\mathrm{CB})$ is the probability of participating in a cereal bank; β represents parameters that must be estimated; $\mathrm{Vc}(i)$ is a vector of a village's preexposure level of social, economic, livelihood, natural, and market characteristics; and ε is an error term. On the basis of the CDDP assignment, we conducted PSM using two subsamples:

- Matching cereal banking villages with CDDP-funded villages that opted for subprojects other than cereal banking (partial control group)
- Matching cereal banking villages with villages that neither benefitted from the CDDP funding, nor had cereal banking schemes (pure control group)

22.3.2 The Propensity-Score Matching Results

Data for the PSM were obtained from the 2003 National Population Census data and National Agricultural Sample Survey 2007. From a total of 827 villages in all the six rural regions in the Gambia, 22 pretreatment village variables were generated for our PSM. Relative to the sample size of the treatment group (35), the large sample size of possible control villages (780) ensures that the pretreatment mean differences between the treated and their matched counterfactuals converge to zero (Chabé-Ferret 2010), thus reducing sample selection based on observables (Baker 2000; Heckman et al. 1997). A one-to-one nearest-neighbor matching algorithm without replacement was employed as it enhances efficiency and reduces biases (Caliendo and Kopeinig 2008, p. 9). It also matches each treatment village to a unique village from the pure control and the partial control groups.

The results of our PSM indicate the variables that influenced the villages to choose cereal banking. Overall, the R^2 indicates that our PSM model [Eq. (22.1)] has strong explanatory power for the probability of a village choosing cereal banking. Out of the 22 variables, 13 were statistically significant at 10 % significance level, while 9 were statistically significant at 5 % significance level. Our coefficients are expressed in odd ratios and not in marginal effects, but the p values indicate the level of significance for each of the variables (Table 22.1).

The PSM results provide the following insights:

- Coefficient of variation of the prices[4] (Huchet-Bourdon 2011) of the main food crops in a village market, or in the market closest to the village,[5] indicates price dispersion and price risk. Our results show that communities facing high price risk tend more to choose cereal banking. This is in agreement with existing studies (Bhattamishra 2012; Cortès and Carrasco 2012).

Table 22.1 Results of propensity-score matching

	Partial control PSM		Pure control PSM	
Variable	Coefficient	$P > \|z\|$	Coefficient	$P > \|z\|$
Coefficient of variation (rainfall)	13.8706	0.286	16.076	0.246
Coefficient of variation (price)	660.3531	0.006**	681.091	0.018*
Poverty	7.2494	0.035*	2.695	0.408
Availability of fruit trees	−0.0512	0.033*	−0.043	0.102
Millet grown	0.00134	0.004**	0.001	0.009**
Proportion of crop farmers	46.2541	0.029*	32.713	0.053
Average HH size	0.7248	0.209	−0.283	0.501
Prop of Hhs without daily market	0.1836	0.046*	0.152	0.058
Prop of Hhs without improved trans.	0.5373	0.009**	0.476	0.038*
Dominant ethnicity gr. 3	14.6823	0.003**	7.953	0.09**
Dominant ethnicity gr. 2	7.4451	0.004**	3.842	0.113
Connected and lowland villages	1.1066	0.109	1.618	0.039*
Distance to market	0.5274	0.038*	−0.446	0.033*
Proximity of the LGA	33.20208	0.024*	33.592	0.02**
Proximity of the district	2.873271	0.021*	−3.023	0.016*
Cov_Price2	1128.559	0.004**	−1157.499	0.016**
No. of observations	451		422	
R2	0.4549		0.3947	

$*P < 0.05$, $**P < 0.01$

[4]See Huchet-Bourdon (2011).

[5]The price data is collected from 28 markets in the Gambia on a monthly basis.

- Access to market is measured by the distance from a village to the closest weekly market. The availability of improved transport systems indicates if a village is connected or remote. The more isolated a community is, the higher the probability that it will choose cereal banking. This is similar to findings of existing studies (Afrique Verte 2010; Bhattamishra 2012). A great distance to markets may motivate communities to store food because households in these villages may incur high transaction and transportation cost, Daviron and Douillet 2013).
- The probability of choosing cereal banking is significantly different between communities with food surplus and those with food deficit (Bhattamishra 2012; Cortès and Carrasco 2012). Lowland villages, which are in close proximity to the River Gambia—a source of fresh water for irrigation—often have more favorable environment for farming (Ceesay 2004; von Braun et al. 1989). In most cases, they produce more food crops, especially rice, relative to the villages located in the upland. A review of the choice of subprojects for the CDDP show that most of the communities in the lowlands opted for production enhancement equipment, access to fields, and gardening, rather than cereal banking (Arcand et al. 2010).

In general, the results of the PSM show that villages that are poor, remotely located, and susceptible to rainfall and price volatility are more likely to choose and maintain a cereal banking schemes (Cortès and Carrasco 2012; Bhattamishra 2012). This highlights the importance of targeting the right villages when implementing a program since not all communities equally need, or can sustain, a cereal banking schemes.

The *T*-test (in Annex on Table 22.5 below) shows that before matching, some significant differences between treated and non-treated villages were observed. However, after matching, there are no significant differences between the two groups. Unlike earlier researches that used PSM, our method gives superior results because the PSM is built on both stratification and randomization (Arcand et al. 2010; Abebaw and Haile 2013). Using propensity-score nearest-neighbor matching, we were able to generate a control group similar enough to the treatment group, so that the impacts of cereal banks can be evaluated.

22.4 Impact Evaluation

Based on the PSM results, 134 villages were selected for the survey. Then we randomly selected 10 % of the households in each village (a total of 460 households). Using this cross-sectional data (Olken 2012), we estimated the average treatment effect (ATE) and the average treatment effect on the treated (ATET). Our analysis focuses on indicators of food security, nutrition security, and livelihood security. Taking our cue from recent literatures about the conceptualization and measurement of food and nutrition security (Hoddinott 1999; Pangaribowo et al. 2013; Pieters et al. 2013; Laborde Debucquet et al. 2013; Kalkuhl et al. 2013;

von Braun and Tadesse 2012), we considered various aspects of food security: availability, accessibility, utilization, and stability.

22.4.1 Empirical Strategy

In the first set of analysis, we compared the mean outcomes to determine if there are any differences in DIM between the treatment, pure control, and partial control groups. This is to determine if any of the effects can be reasonably attributed to the treatment. Since the pretreatment characteristics of villages were considered in the matching process, any differences in the outcomes can be attributed to the treatment (Ravallion 2007). Therefore, the DIM indicates the ATE.

22.4.2 Comparison of Means: Treated and Control Villages

As in the PSM, we found that most of the villages remained unchanged in their physical and socioeconomic features 4 years after implementing the project. This further validated our PSM. However, among villages, there are also some important DIM, some of which indicate the ATE of the program (Becker and Ichino 2002).

The households had a food gap of more than 2.5 months on average. The food gap, also called the lean period or hungry season (FAO 2011), represents the number of months a household reports not having adequate food stocks or money to buy food. The households often need to hire out their own labor for money or to take out a loan. We observed significant differences in the length of lean period among the households sampled.[6] While households in treated villages experienced an average 2.1 months of food gap, the pure control group experienced almost 3 months of food gap, and the partial control group 2.5 months. Comparing the treated group and the pure control group, cereal banking reduces the length of lean period by 25 %.

The results for the selling prices of cash crops (groundnut at harvest) and the buying prices of food crops (millet and maize during the lean period) also indicate a significant difference between the treatment and control villages. The price effect is more significant when comparing treated villages and partial control villages. This indicates that variations in food and cash crop prices is higher in partial control villages than in the other two groups, suggesting that in the absence of a food storage, households may produce more food and yet achieve lower incomes. Variation is defined as the difference between prices of food crops (rice, maize, and millet) reported in August (lean period) and price of cash crops (groundnut) reported in December (harvest period) minus the yearly average prices of the same crops.

Figure 22.3 shows that at harvest, when most rural households are net sellers, the selling prices of excess production are 16 % lower in control villages than treated villages. In contrast, during the lean period, when most rural households are net

[6]The lean period or hungry season in the Gambia often starts in July–September.

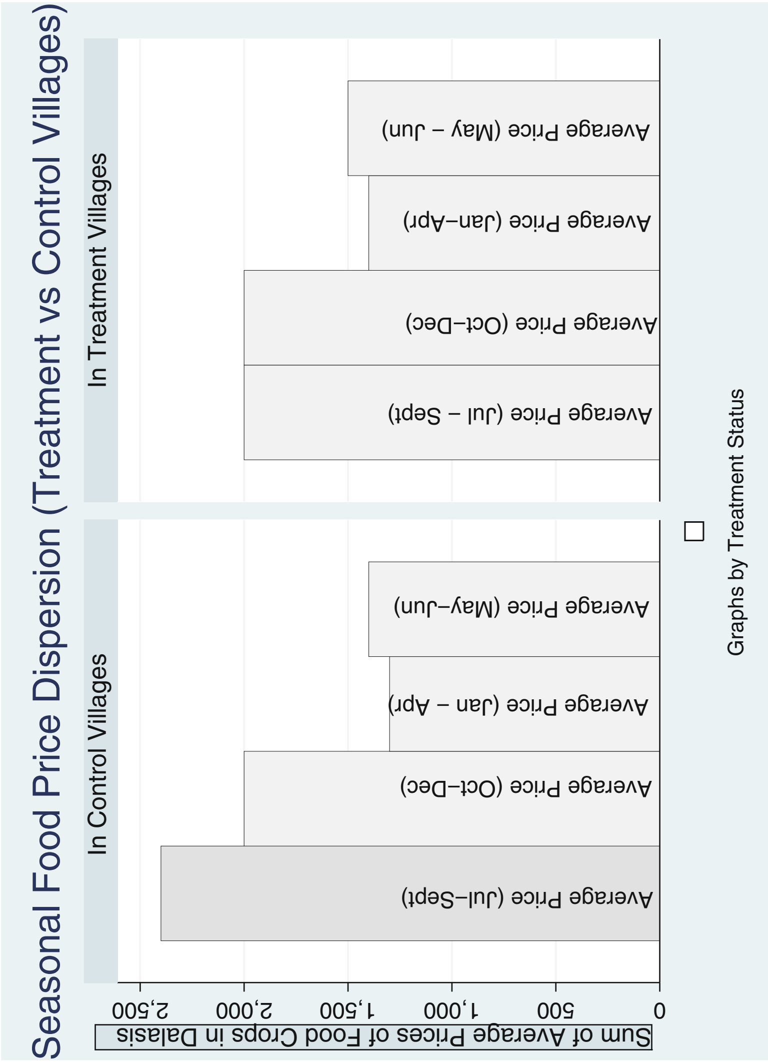

Fig. 22.3 Seasonal food dispersion across treatment status. *Source:* own illustration

buyers, the buying prices of cereals are significantly lower in control villages than treated villages (about 15 % lower). This implies selling farm produce at lower prices and buying food at higher prices for households in control villages compared to those in treatment villages, contrary to conclusion in Kent (1998).

The following may explain the differences in prices and price variability:

- Households in treated communities reported higher dependency on their own production for food than those in control group. Thus, treated communities sell less of their food crops at harvest and buy less food during the lean period, signifying that they become net buyers of food much later than the control group.
- Cereal banking schemes disincentivize speculative arbitrage, often carried out by middlemen, moneylenders, and input lenders (Cortès and Carrasco 2012; Kent 1998). As shown in the DIM in Table 22.2, middlemen are more active in control villages than in treated villages. In the Gambia, middlemen and moneylenders lend food or inputs to households. Similar to the findings of other empirical studies in this field (Cole et al. 2012; Morduch 1995; Cortès and Carrasco 2012), it was observed that when risk management strategies or one form of credit scheme are in place, there will be less demand for other forms of credit (Gilbert 2012).
- Similar to other research findings, inter-seasonal price changes are more significant for domestically produced food (millet and maize). Compared to other similar studies (Afrique Verte 2010; von Braun et al. 1999; Bhattamishra 2012), this study found a slightly lower, but nonetheless significant, inter-seasonal price change between harvest and lean seasons: 53 % in treated villages and 84 % in control villages. The treated villages showed a 31 percentage point reduction in inter-seasonal price variation.

Table 22.2 Mean outcomes—treated and control villages

	Treated	Pure control	Test	Partial control	Test
Food gap	2.170	2.830	0.000**	2.490	0.047*
Price cash crop—harvest	726.470	625.000	0.003**	587.230	0.000**
Price food crop—lean	918.570	1057.970	0.002**	959.780	0.177
Variation[a] in cash crop prices—harvest	−178.180	−192.910	0.350	−246.660	0.026*
Variation in food crop prices—lean	114.280	262.640	0.000**	238.630	0.000**
Price of imported rice	1159.14	1155.850	0.775	1153.640	0.639
Self-help groups	1.9	1.6	0.665	1.7	0.872
Ward Development Committee membership	2.645	1.927	0.894	1.979	0.895
Moneylenders/middlemen	1.4	1.72	0.025	1.68	0.482
Number of villages	35	48		55	

*$P < 0.05$, **$P < 0.01$

[a]Variation in cash crops at harvest and food crops at the lean period are the difference of the price at harvest/lean minus the mean price during the year

Our study also found that there are more local self-help groups in the treated villages than the control villages. This indicates that when compared to the control villages, the treated villages are likely to have created more internal networks and have better capacity to initiate, implement, and sustainably manage their self-help projects. The treated villages are also significantly more socially connected, having much more representation in ward- and district-level organizations, such as the Ward Development Committee (WDC).

In addition, households in the treated villages tend to be more effective at adapting to changes (Maxwell and Smith 1992) than their counterparts in the control villages. For example, treated communities were more likely to introduce new varieties of crops and use extensive production systems (although the latter is not always sustainable), and their population less likely to migrate.

22.4.3 Estimating Treatment Effect on the Treated

To evaluate the impact of the cereal banking scheme, we conducted a regression analysis to estimate the actual ATET or the intention to treat (ITT) (Arcand et al. 2010; Duflo et al. 2007).

Our regression model at village level can be described using the equation:

$$Y(i) = \alpha(w) + \pi V(i) + \beta T(i) + \varepsilon(i), \tag{22.2}$$

where $Y(i)$ is the outcome variable of village i, α represents baseline village characteristics which allows for estimation with and without fixed effects (w), $V(i)$ is a vector of village level characteristics, T is the cereal bank dummy ($T = 1$ if treated, 0 otherwise), and $\varepsilon(i)$ is the error term. α is the baseline outcome, and π and β are parameters that need to be estimated. The dummy T is included in Eq. (22.2) to assess the impact of the CDDP treatment on treated and partial control villages. We also estimate the models using fixed effects, comparing the treated villages with the pure control and partial control villages. The combination of fixed-effect estimation and propensity-score matching reduces the selection bias caused by time-invariant missing variable endogeneity or selection on unobservable bias (Duflo et al. 2007).

Two main indicators are identified after reviewing current literature on food and nutrition insecurity.

Food Gap Effects

The food gap, a proxy for food availability, is the number of months in a year households report having inability to satisfy their food needs (Maxwell and Smith 1992). Households and communities in the Gambia with food deficit experience food gap because of the unavailability or high cost of food during the lean period. This affects food and micronutrient intakes as well as farm investments and yields. We therefore use the food gap as a measure of household food availability.

Comparing with pure control and partial control villages, villages with cereal banks saw a significant reduction in food gap, with and without fixed effects

(Table 22.3). Middlemen reduce the food gap as well, even though the extent of their influence is debatable. The distance of a village to a main road, which is a proxy for market access, is positively correlated to the food gap.

The further away a village is from lowland areas, the larger the food gap is. This is understandable since lowland areas have higher crop-growing potentials and can allow for off-season gardening (Ceesay 2004). Some of the lowland villages are also able to practice double cropping of rice (von Braun et al. 1989; Carney 1992).

The prices of food crops during the lean period (July–September) also significantly increased the food gap in all cases. Thus, managing inter-seasonal prices could be an effective way of shortening the lean period in rural areas of the Gambia.

Although the CDDP intervention reduced food gap, it does not significantly shorten the lean period. This is because the CDDP had various other community subprojects, some of which may not have a direct and immediate impact on food production and smoothing consumption. Using fixed effects is important because it increases the precision of our model, evident in the R^2 and the standard error values of our treatment variables.

Price Variability

Inter-seasonal changes in prices of the three major crops in the Gambia[7] is a proxy for food accessibility. In Amartya Sen's book *Poverty and Famines* written in 1981, he argued that the problem of hunger or food insecurity is not only about food availability, but there could also be structural, cultural, or economic circumstances that deny some people access to food, even when food is available. Thus, some of the key indicators of food insecurity include household income, food prices, and household expenditure (von Braun 2011). High food prices during the lean period inhibit food-deficit poor households from buying and consuming adequate amount of food (Gilbert 2012). When food prices are high, poor households in rural areas often adopt various strategies to alleviate the situation. These strategies include reducing frequency and quantity of food intake, foregoing other basic needs, and taking out loans or working to purchase food. The strategies can, however, further exacerbate their indebtedness and poverty (Action Aid 2011). To capture the changes in inter-seasonal price variability, we constructed a price variability model:

$$\text{Log}\,(P_{\text{l}}–P_{\text{h}}) = \alpha(w) + \pi V(i) + \beta T(i) + \delta \text{CDDP}\,(i) + \varepsilon(i), \tag{22.3}$$

where P_{l} and P_{h} are prices of food crops during lean period and harvest period respectively.

Our results in Table 22.4 show that cereal banking leads to a significant reduction in the inter-seasonal food price deviation between harvest and lean period. The

[7] Rice, millet, and groundnut

Table 22.3 Food gap

	(1)	(2)	(3)	(4)	(5)
	Food gap Treatment dummy	Food gap CDDP dummy	Food gap District fixed effects	Food gap Pure cont plus FE	Food gap Part. cont plus FE
Treatment	−0.515 (0.194)**	−0.473 (0.214)*	−0.470 (0.216)*	−0.509 (0.250)*	−0.366 (0.322)
CDDP villages		−0.082 (0.175)	0.036 (0.181)		
District 9 (Fulladu)			−1.296 (0.456)**	−0.960 (0.665)	−1.044 (0.711)
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	112	112	112	73	71
R-squared	0.40	0.40	0.50	0.54	0.54

Standard errors in parentheses *significant at 5 %; **significant at 1 %

NB: district 9 (Fulladu East) is a rice growing area in which some villages have access to irrigation

Table 22.4 Price variability

Variables	(1) Log price dev Treatment dummy	(2) Log price dev CDDP dummy	(3) Log price dev District fixed effects (FE)	(4) Log price dev Pure cont plus FE	(5) Log price dev Part cont plus FE
Treatment	−0.412***	−0.406***	−0.436***	−0.435**	−0.411**
	(0.121)	(0.132)	(0.121)	(0.179)	(0.172)
Middlemen	0.250**	0.249**	0.144	0.262	0.128
	(0.100)	(0.101)	(0.112)	(0.170)	(0.190)
District 9 (Fulladu)			−0.478**	−0.447	−0.552
			(0.238)	(0.348)	(0.363)
CDDP villages		−0.0116			
		(0.0986)			
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	113	113	113	74	71
R-squared	0.593	0.594	0.669	0.717	0.701

$^{*}P < 0.05$, $^{**}P < 0.01$

coefficient on the treatment indicates that cereal banking reduced inter-seasonal price changes by an average of 41 %.

Similar to findings in another study (Oguoma et al. 2010), our results show that the speculative behavior of middlemen increases inter-seasonal food price variability. The influence of middlemen on the market, prices, and food security at the local level is debatable; most evidence indicates that middlemen exploit farmers and erode profits. Oguoma et al. (2010) argued that the intervention by middlemen increases buying prices for consumers and reduces selling prices for producers, lowering the farmers' profit margins. Often the middlemen engage in temporary arbitrage (Kent 1998), which may also cause the food prices to increase further. This negatively affects the food security of farmers, who shift from being net seller at harvest to net buyers during the lean periods (Bhattamishra 2012).

The district dummies in the fixed-effect model highlighted the importance of double cropping, a practice applicable to district 9 (Fulladu East). In contrast to district 1, district 9 saw a reduction in the inter-seasonal price deviation and food gap.

Other social indicators are changes in demographic characteristics, population growth, and membership in Ward Development Committee (WDC)—a proxy for social capital (Jaimovich 2012). The cereal banking scheme provides a platform for debates about community actions, and gives members an opportunity to organize and manage a program for their community. Over time, the social interaction within a community may enhance intra-village social relations and build the capacity of the community to participate and contribute to other development initiatives.

22.5 Conclusion

The results support the hypothesis that cereal banking is an important part of enhancing the food and nutrition security of communities by improving food availability, accessibility, and stability. Cereal banking could reduce food price variability and food gap by more than 25 %. This can be attributed to communities having sufficient food during the lean periods, thus reducing speculations.

While community cereal banking schemes may be effective in addressing inter-seasonal price variations and idiosyncratic risks, they are less effective against covariate risks, especially climate risks. In addition to the risk of embezzlement, there is a high failure rate during periods of poor rainfall.

The results of the propensity-score matching analysis emphasize the need to target a program at appropriate villages based on village characteristics, which influence the choice, sustainability, and impact of the program.

Compared with food aid or humanitarian aid, cereal banking is a more engaging solution that helps vulnerable communities to secure their livelihood and build up their resilience. It empowers affected households to participate and take up ownership. Thus, it could be an effective and participatory channel for food aid delivery during drought. This is very important because price and climate risks are reoccurrences (Cortès and Carrasco 2012).

While food reserves at the macro level require more careful management and present a large logistical and financial challenge, cereal banking at the community level has the unique advantage of being less cumbersome—the closer proximity to vulnerable communities results in lower transportation and administrative costs (Coulter 2009).

Appendix

Table 22.5 Test of differences (matched treated and control villages)

Variable	Sample	Treated	Partial control	*T*-stat	Treated	Pure controls	*T*-stat
Coefficient of variation—price	Unmatched	0.2647	0.2428	2.92	0.264	0.247	1.68
	Matched	0.2644	0.2625	0.19	0.264	0.266	−0.18
Poverty index	Unmatched	0.7061	0.6543	2.7	0.7061	0.6604	2.262
	Matched	0.7061	0.732	−1.23	0.7061	0.705	0.053
Millet grown	Unmatched	227.289	148.82	2.15	227.29	170.247	1.41
	Matched	227.289	221.77	0.08	227.29	178.034	0.8
Availability of fruit trees	Unmatched	4332.19	5795.61	−1.61	4332.191	5281.032	−1.13
	Matched	4332.19	3811.68	0.76	4332.191	3165.702	1.83
Pp of crop farmers	Unmatched	0.9657	0.921	4.14	0.966	0.927	3.76
	Matched	0.96574	0.9681	−0.41	0.966	0.97	−0.83
Av. HH size	Unmatched	11.419	11.12	0.62	11.419	11.245	0.35
	Matched	11.419	11.64	−0.33	11.419	11.71	−0.44
No daily market	Unmatched	81.476	62.65	4.24	81.477	66.731	3.46
	Matched	81.47	82.54	−0.27	81.477	80.683	0.2
Distance from market	Unmatched	43.308	41.83	0.55	43.309	40.949	0.9
	Matched	43.3	45.168	−0.77	43.309	44.634	−0.53
HHs without improved transport	Unmatched	98.22	91.72	3.43	98.23	92.968	3.06
	Matched	98.229	97.668	0.54	98.23	97.415	0.72
Remote and upland villages	Unmatched	0.5106	0.4108	1.31	0.5546	0.4208	1.88
	Matched	0.5106	0.5106	0	0.5546	0.55	0

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Stocks and Storage Behavior of Traders in Ghana: Insights from a Trader Survey

23

Lukas Kornher and Felix A. Asante

23.1 Introduction and Motivation

Grain markets in many African countries exhibit large price volatility which is driven by strong seasonality. Seasonal production and limited storage are identified as major causes of intra-annual price variation (Jones 1972; Sahn and Delgado 1989). Price spikes often occur as a consequence of stock-outs at the end of the marketing season (Shively 2001; Osborne 2004; Tadesse and Guttormsen 2011). The adverse consequences of seasonal hunger and poverty are well acknowledged, and functional markets are recognized as a prerequisite to resolve these problems (Vaitla et al. 2009; Maxwell 2013; van Campenhout et al. 2015).

The structure and efficiency of markets have been improving since the liberalization process in the 1980s. But the price surges and international food crisis in 2007/2008 brought grain marketing and public intervention back on the agenda of policymakers around the world (Kaminski et al. 2014). This is partly driven by the lack of confidence in free markets and the competitive behavior of traders (Osborne 2005; Sitko and Jayne 2014) and a growing fear for the political economy of food prices (Arezki and Brückner 2011; Brückner and Ciccone 2011). Governmental interventions in the form of price stabilization programs and trade policies are often made without profound knowledge of the marketing system. "Under these circumstances, [...] interventions [are likely to] impair the functioning of the system more than they improve it" (Jones 1972, p. 4). Thus, evidence-based research is

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M. Kalkuhl et al. (eds.), *Food Price Volatility and Its Implications for Food Security and Policy*, DOI 10.1007/978-3-319-28201-5_23

indispensable to endow policymakers with adequate information so that they can design successful agricultural policies aimed at enhancing food security.

In this study, Ghana is chosen as a country case study as it is a typical sub-Saharan African country in many respects. Although the country has made considerable progress in poverty alleviation and the fight against hunger over the past 20 years, food price volatility in the country remains among the highest in the world, and seasonal food insecurity prevails in many parts of the country, especially the north (Quaye 2009). On the other hand, Ghanaian markets are at a crossroad. Wheat and rice imports are becoming more important with a growing free-spending middle class. Poultry and fish farming as well as increasing demand for processed food items shifts market shares toward the industrialized food sector. These changes will undoubtedly make an impact on the traditional marketing system.

The empirical literature on grain markets in Ghana is divided. On the one hand, time series econometrics approaches are used to explain the dynamics and variability of wholesale market prices (Alderman and Shively 1996; Shively 1996, 2001) and spatial market integration (Badiane and Shively 1998; Abdulai 2000). All of the above-mentioned studies focus on maize, the most important domestic crop in Ghana. On the other hand, market analyses based on survey data stress the role of the various actors in the value chain. Much of these studies are of qualitative nature and give insights on marketing channels, spatial trade patterns, and transaction costs (Alderman 1992; Armah and Asante 2006).

None of the existing studies examine storage behavior of larger wholesale traders and companies in order to predict national stocking trends, which is the main objective of this chapter. This is of particular importance since wholesale traders play a key role in guaranteeing sufficient food supply throughout the year. The present work fills this gap in the literature by evaluating primary data collected from July to November 2013. This contains quantitative data from a survey among wholesale traders with significant storage capacity on their operation in spatial trade and intertemporal storage. Qualitative interviews were conducted with processing companies, market experts, and other relevant stakeholders. The information is put into context and policy implications are deduced. In doing so, the findings can also be seen as a starting point and input for future research.

23.2 Price Instability and Trade Patterns

There is a natural imbalance between the production and consumption of agricultural commodities. More specifically, consumption is primarily stable, while production is highly volatile, in particular in rainfed agricultural systems, which are the predominant type of agricultural system in many African countries. Therefore, commodity prices are subject to natural instability. Besides, the seasonality of production requires intertemporal arbitrage and causes a deterministic price gap between harvest and lean season, owing to the costs arising from storing food between the seasons.

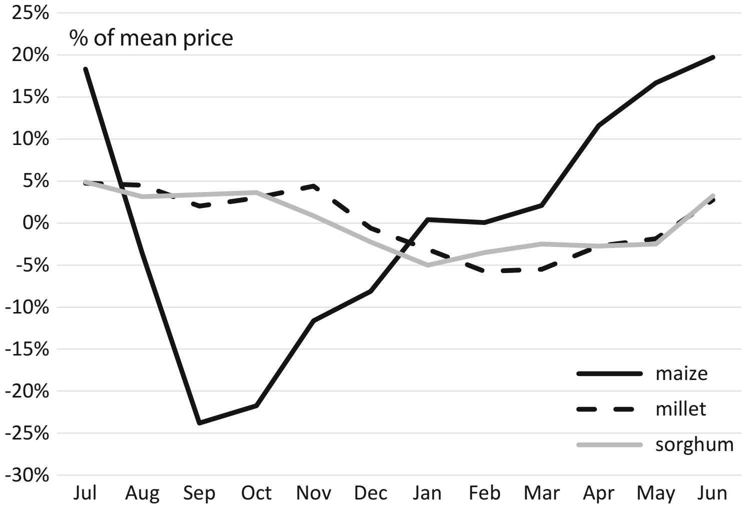

Fig. 23.1 Seasonality of local staples. *Source*: Authors' computation based on SRID (2014)

Ghana is no exemption in this respect. In order to distinguish irregular price variability from the fixed seasonal trend, we applied an Unobserved Component Model to market-level wholesale price data. The average seasonal price trend for locally produced grains is shown in Fig. 23.1.

Seasonal price instability is highest for maize, with a seasonal gap of more than 40 %, followed by millet and sorghum, with around 10 %. As proposed by the theory of storage, the inter-seasonal price gap is solely attributed to the cost of storage, since market demand and supply equate prices between two periods. (Williams and Wright 1991). Alternatively, market failures, such as the lack of insurance markets to hedge against price risks, are identified as the reason for limited storage, causing inadequate supply (Newbery and Stiglitz 1981). In line with this, wholesale market prices exhibited at least three major price spikes during the last 15 years. All these spikes were transitory and persisted for 1–2 months only. This hints at temporal supply shortage at the end of the marketing year as a consequence of traders' stock-outs (Shively 2001).

Generally, markets within Ghana are found to be well connected, but high transportation costs (due to poor infrastructure) impede full market integration (Abdulai 2000; Quaye and Ameleke 2008; Cudjoe et al. 2010) and link asymmetric adjustment between prices in the central and local markets to inventory adjustment of traders. Therefore, storage decisions are made by taking into account the current and future prices at distant markets, which affect stocking decisions via spatial and temporal arbitrage conditions, as illustrated in Fig. 23.2.

In addition to this, prices are driven by annual domestic production levels and the prospect of speculative exports to neighboring countries (Shively 1996). International prices are likely to have limited impact on domestic price dynamics,

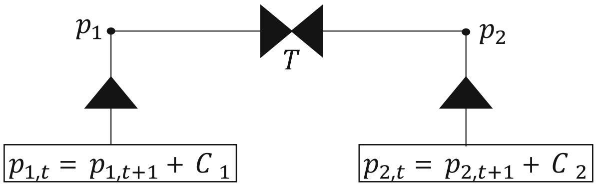

Fig. 23.2 Schematic representation of equilibrium price equations. *Source*: Adapted from Roehner (1995). *Note*: T denotes transport costs between market 1 and market 2, while C_1 and C_2 are costs of storage in both markets. In theory, spatial and intertemporal arbitrage take place only when price differentials exceed costs. The equilibrium price conditions induce interdependencies between current and future prices in different markets

which is related to the minor relevance of international and regional imports (Conforti 2004; Cudjoe et al. 2010).[1] By contrast, domestic rice production makes up only about 30 % of the total national supply, causing local rice prices to follow the price dynamics of imported rice without noticeable seasonality (Amikuzuno et al. 2013). A 20 % import tax (10 % for wheat) is imposed on all food commodities; the import duty was suspended for rice in 2008 and 2009. In addition to that, port charges further increase the price of imports and limit the linkage to international prices (Minot 2011).

Last, food markets in Africa are often publicly regulated by national food companies that are also involved in food marketing. Historically, Ghana's agricultural sector has been characterized by large state involvement by the Ghana Food Distribution Cooperation (GFDC) and the Grain Warehousing Company (GWC).[2] After a short period of complete market liberalization, the National Food Buffer Company (NAFCO) was founded in 2010 to manage the country's emergency and intervention stock. Public stocks are accumulated through market purchases at predetermined prices, while distribution is arranged when market prices exceed target thresholds. Benin et al. (2012) review the operations of NAFCO but are unable to assess its impacts on price dynamics. The main problem is the non-transparency in the operational decision-making by NAFCO. However, target stock levels only represent a small portion of the annual production, and thus NAFCO's purchase and release decisions are unlikely to influence market prices directly.[3] In contrast, the determination and public announcement of the minimum guaranteed price (paid

[1]Food prices are also affected by high inflation pressure, which is considered the major challenge to macroeconomic stability. After a short period of single-digit inflation, the growth rate of the consumer price index has returned to a level of above 10. In accordance with this, the Ghana Cedi (GHS) has depreciated greatly since 2013. The exchange rate is free-floating since 2006, while a redenomination was implemented in 2007 by canceling four digits (1 GHS = 10,000 GHC). GHC: Ghana Cedi; GHS: New Ghana Cedi.

[2]See Sijm (1997) for a comprehensive overview.

[3]NAFCO stock levels are (1) operation stocks, maize (30,000 mt), rice (15,000 mt), and soybeans (1000 mt), and (2) emergency stocks, maize (10,000 mt), rice (10,000 mt), and soybeans (1000 mt).

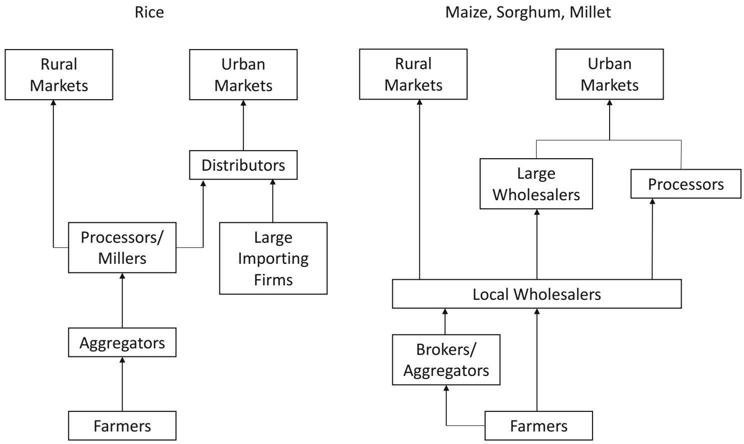

Fig. 23.3 Outline of the value chain of important staples. *Source*: Authors' illustration

to farmers) have an impact on markets because they can strengthen the bargaining position of farmers in negotiations with traders.

The differences between rice and the three other food commodities—maize, sorghum, and millet—are also reflected in the characteristics of their respective value chains, which are depicted in Fig. 23.3. The distribution of imported rice differs substantially from the marketing of locally produced crops. A few large importing companies divide the majority of the market among themselves (Kula and Dormon 2009). They sell their rice stocks to wholesale traders and supermarkets around the country through their wide local distribution network, but they also run their own outlet stores. Their business activities are highly industrialized and include the operation of large warehouses around the country.

In contrast, the locally produced rice is usually marketed via two distinct channels: first, through aggregators and local wholesalers/processors for sales in rural markets; second, via larger wholesale traders to markets in urban centers. For small and medium size farmers, rural assemblers act as collectors who aggregate surpluses and then sell them to wholesalers in larger towns. Then, wholesale traders sell the produce not only to processors, millers, and retail traders but also directly to consumers. In contrast, larger farmers tend to sell their produce directly to wholesale traders. Maize, sorghum, and millet also pass through the hands of the food industry on their way to becoming final consumer goods; the proportion of formal trade for maize is substantially higher than for millet and sorghum.

Since no value is added to the commodity by having multiple agents involved in the value chain, farmers earn higher profits when selling to wholesale traders directly (Sitko and Jayne 2014). Furthermore, the literature acknowledges that traders play an important role in the functioning of markets in that they provide farmers with inputs and credits (Antons 2010; Sitko and Jayne 2014). There is also little evidence that the market structure of domestic grain trading is noncompetitive, apart from the high concentration among few large rice-importing firms (Abdulai 2000; Swinnen et al. 2010; ACET 2014). It is to note that retailers in urban centers usually organize themselves into associations. In doing so, market queens, the elected heads of these female retail trader groups, have manifested themselves as an influential counterpart to wholesale traders (Langyintuo 2010).

Transporting commodities from surplus regions in the middle belt and the northern part of the country to consumption and industrial centers is the major challenge for a long-distance trader. Poor road infrastructure is reflected in the long travel times needed for a relatively short distance. Compared with the well-understood structure of the value chain, research about how marketing and trade flows change in the course of a year is still lacking. In other words, it is clear how grain finds its way from producers to consumers, but little is known about how the grain gets from harvest to lean season. Precisely, the agent who stores the grain and the amount and time frame of storage are still unknown. Furthermore, the heterogeneity among wholesale traders is not well considered.

To understand both the spatial distribution and seasonal patterns of storage behavior, it is crucial to start by examining the marketing behavior of farmers. Without providing exact figures on the quantities, farmers' sales of all types of grains exhibit strong seasonality, with a peak after harvest (GSS 2007; Chapoto et al. 2014). From past surveys, it is well known that only a portion of production is formally traded (Armah and Asante 2006; EAT 2012). Therefore, the actual share of stocks held by traders is presumably low (Jones 1972; Alderman 1992). In contrast, the observed increment in the market purchase made by farmers indicates that commodities must be stored somewhere and then sold back to farmers at the end of the marketing year (GSS 2007; Chapoto et al. 2014).

Moreover, there are also massive changes happening in Africa's food marketing. On the one hand, the introduction of modern telecommunication technologies drastically reduces transaction costs (Overa 2006; Tack and Aker 2014) and also eases market access for farmers and small traders. On the other hand, food markets are becoming increasingly industrialized. The number of supermarkets is growing, and with it comes an increasing demand for processed final consumer goods. For this reason, food processing companies are increasing their production volume and claiming a larger share of marketed production. This has wide-ranging consequences on grain marketing. First, the industrialized sector prefers to make purchases in large quantities in order to reduce transaction costs. Second, quality standards gain importance, and this presents challenges to proper handling by value chain actors. Third, retail companies will affect the whole market structure and are likely to occupy a prominent position in the market. The trading sector will be compelled to adjust to these developments in order to preserve its role in the marketing system.

23.3 Storage Behavior

23.3.1 Description of the Data

The analysis of storage behavior in Ghana is largely based on a trader survey which provides quantitative data on grain storage and trade. The survey was undertaken as a joint research between the Center for Development Research (ZEF) and the Institute for Statistical, Social and Economic Research (ISSER) at the University of Ghana, Legon, and was held at major market sites in Ghana between August and November 2013. Subsequent to the survey, follow-up telephone interviews were conducted in April and May 2014. Qualitative information from a baseline survey in 2012 and from consulting experts during August and November 2013 enrich and underpin the quantitative data.

First, there are no business directories for traders in Ghana. The lists of traders identified during the research contained invalid phone numbers and information about companies that no longer exist. Therefore, randomization-based sampling techniques were inapplicable. Second, the total number of traders who engage in intertemporal arbitrage is not large, and a larger sample size is considered to be better. For this reason, the sampling was conducted with the intention to create a sample that is representative of the aggregate market behavior. Traders were identified using two unofficial lists: a list of NAFCO contractors published on its webpage and the business directory of Ghana Web, an online news platform.[4] Contact information of traders was also obtained from governmental publications and other publicly available documents. Furthermore, snowball sampling was used in order to increase the number of respondents.

Generally, traders were contacted by phone and asked about their willingness to participate in the survey. In this way, the response rate was close to 100 %. For the follow-up telephone interviews, the respondents of the first survey were contacted. The interviews were structured as follows: First, general information on the enterprise was collected. The second part of the interview aimed at obtaining a general overview of grain trading activities. The heart of the questionnaire was the section about storage activities; in this section, respondents were asked to state their purchases and historical inventory levels during the prior marketing year, that is, 2012/2013. Third, respondents were asked to evaluate specific statements to deduce their perception of risk associated with storage. Last, the interview ended with a survey on the traders' expectations of future price changes, and this section also assessed the traders' market knowledge of tariff rate and historic rainfall and geographical production patterns. Moreover, the telephone interview also asked traders to evaluate specific factors that influence price dynamics and induce market risk. The interview also attempted to obtain information on different cost components.

[4] Available at http://www.ghanaweb.com/GhanaHomePage/telephone_directory/.

In total, 36 traders were surveyed in the first round. Only 20 traders were ready to answer to the telephone questionnaire. Several qualitative interviews were also conducted; most notably are interviews with processing companies and practitioners. Since farmers hold a substantial amount of stocks, it is essential to incorporate their behavior into the analysis. The Ghana Living Standard Survey (GLSS) contains an exhaustive section on agriculture, including a section on the seasonality of sales and market purchases. Nevertheless, a few qualitative interviews with farmers and farmer associations were conducted. The ZEF-ISSER Trader Survey is different from most existing trader surveys in two respects. First, this survey focused on interviewing traders who engage in intertemporal arbitrage rather than spatial arbitrage or retailing. Second, related to the first point, intertemporal arbitrageurs who own or rent warehouses are sometimes large companies which are also involved in other businesses. Consequently, the average storage capacity of the respondents is around 10,000 metric tons (mt), and roughly 60 % of the traders had at their disposal storage facilities of 500 mt and above. Apart from inference about the aggregate storage behavior of the market, information on individual stocking trends and trader characteristics allows individual trading behavior to be analyzed in more detail. For this reason, the presentation of research findings from the survey is divided into these two aspects.

23.3.2 Motives for Trader Storage

23.3.2.1 Speculative Storage

As predicted by the economic theory, the most prominent motive for storage is the speculation on a future price increase. Speculation is defined as the engagement in risky transactions to benefit from fluctuation in market values. The supply of storage model is extensively discussed in the literature and widely accepted as best way to describe the price dynamics of storable commodities. In brief, storers would choose to provide additional storage as long as the marginal costs of storage do not exceed the expected return from storage in the subsequent period. Generally, it is possible to hedge against any risk associated with storage by trading future contracts or through informal forward contracting. In this way, the price risk is transferred to another institution. However, commodity exchanges and forward contracting are uncommon in most developing countries. Anticipated stocks are a special variant of speculative stocks. They are not held for speculation of higher prices but in anticipation of changes in demand (Minner 2000). Rice traders in Ghana reported keeping anticipated stocks by increasing their stocks before Christmas and Easter to satisfy the increase in demand (ZEF-ISSER Trader Survey 2013).

Speculative storage should not be confused with hoarding, which food traders are often accused of in times of scarcity in the market. The literature defines hoarding as excessive speculation. In theory, hoarding can only arise from imperfect competition (Osborne 2005) or overestimation of price changes (Ravallion 1985). Under the intertemporal arbitrage condition, two major determinants of storage quantity are price expectations and storage costs. Storage costs are high in many developing countries due to high interest rates. Ghana is no exemption in this respect (Armah and Asante 2006). Therefore, the amount of stocks in Ghana is likely to be substantially lower than in industrialized countries. Commodity prices in Ghana remain largely driven by seasonality (with the exception of rice), as discussed in the previous section. For this reason, speculative returns are unlikely to be realized from interannual storage. The only justification for speculative stocks at the end of the marketing year is given by uncertainty about the timing of the next harvest (Peterson and Tomek 2005). In contrast, high seasonal price variation generates a great opportunity for traders to benefit from intra-annual price changes. In theory, everyone who possesses stocks can participate in speculation. In reality, however, because speculation binds capital for a longer period, mostly larger and highly liquid enterprises are capable of speculative storage. Indeed, the survey reveals that traders who speculate also diversify their risks by being involved in spatial trading to realize low-risk profits. The respondents also noted that stocks need to be depleted before the end of the marketing year because of an anticipated decline in market prices (ZEF-ISSER Trader Survey 2013). In a typical marketing year, speculative stock levels are expected to be highest when prices are lowest. However, traders prefer to store grain stocks at lower moisture levels. For this reason, maize harvested in August/September in the southern parts of Ghana is usually not kept for long, and existing stocks are depleted again before the next harvest comes in.

23.3.2.2 Safety Stocks

Safety stocks are mainly known from the logistic and supply chain management literature. They are describe as extra stocks that are carried to moderate the risk of stock-outs and associated incapability to satisfy demand. The need for safety stocks arises from uncertainty in demand and supply (Guide and Srivastava 2000). Since inventory holding is costly, safety stocks should be kept at a minimum. Optimal safety stocks are chosen depending on uncertainty in demand, supply, and processing time (Minner 2000). In contrast to speculative stocks, safety stocks are not related to expected future prices but rather to the quantity demanded from the enterprise. In the context of Ghana, two types of market participants are likely to carry safety stocks: processors and animal feed manufacturers and traders, especially retailers. A trader survey conducted during October 2013 by the World Food Program (WFP) found replenishment times of the vast majority of retailers and wholesale traders who responded to be below 1 week (WFP 2014). This indicates that the retailers and wholesale traders attempt to possess sufficient stocks at all times. An explanation may be the high importance of maintaining a continual business relationship by fostering confidence through short-term deliveries. This is evident in that 19 out of 36 respondents ranked “the risk of losing business partners when stopping to supply for 3 month” as a high risk (28/36 as medium or high risk) in the ZEF-ISSER Trader Survey, in particular those traders who are less likely to hold speculative stocks. Retailers hold safety stocks to foster long-term relationship with customers. Consumers who are unable to find what they want in a retail shop will presumably buy the goods elsewhere and are less likely to return to the shop because they expect not to find the goods there again. Fafchamps

(2004) emphasizes contractual risk in many African countries as the cause of traders keeping large inventories. The risk of late delivery and poor-quality goods drive firms that experience late delivery to hold more than two times more stocks than firms that do not encounter late delivery. Processing firms in Ghana stated that they have enough inventories to sustain production for 1–2 months (ZEF-ISSER Trader Survey 2013). The rise of supermarkets in many African countries in the past years has changed the agro-food system dramatically, causing a shift toward a greater variety of products. Van Donk (2001) projects that the level of safety stocks will increase in order to satisfy the demand for multiple food products at the same time. By definition, safety stock levels are roughly constant throughout the year and will never fall to zero since they are independent of current market prices. However, stock levels are likely to increase by the end of the marketing year as low availability makes input supply uncertain.

23.3.2.3 Aggregation Stocks

The literature on grain marketing in developing countries emphasizes the importance of small-scale traders at village and town level. They play an important role when many farmers do not have access to markets or the costs of traveling to the market are prohibitively high (Sitko and Jayne 2014). As described above, these assembly traders sell their goods to larger wholesale traders, who transport commodities across the country. The aggregation of stocks is an artifact of the characteristics of the value chain. Wholesale traders are likely to collect only larger quantities from village- and town-level markets. Thus, assembly traders aggregate stocks in order to ensure that the transaction process with their trading partners remains efficient. The aggregation of stocks can also occur at central markets when wholesale traders are asked to aggregate large quantities of stocks (more than 1000 mt) for industrial consumption or purchases made by NAFCO and the WFP, as reported in the survey. This form of stock aggregation is usually performed only when the purchase of the aggregated stocks is guaranteed or even pre-financed. The nature of this form of trade means that stocks will be totally depleted when the target quantity is reached and the goods are delivered to the contractee. There are no reasons for traders not to repeat the procedure several times in the course of a year, yet traders make sure that their stocks are depleted before stocks from the new harvest comes in.

23.3.3 Operational Costs

The profitability of storage depends on the costs of operation. Traders incur direct costs from marketing, transport, and storage (Angelucci 2012). Cleaning, drying, and packaging are usually done at the farm level before the produce reaches the market. The main challenge of proper handling is to reduce the moisture content of fresh crops for storage to decrease the incidence of discoloration (Armah and Asante 2006). In some instances, traders support farmers in this process by providing drying facilities or functional bags for adequate storage (Antons 2010).

Table 23.1 Transport costs on selected roads in May–June 2011

Route	Bag (kg)	Price/bag	Price/mt	Distance	Cost mt/km
Kumasi-Accra	50	2.31	46.28	272	0.17
Kumasi-Tamale	50	2.9	57.83	382	0.16
Kumasi-Ejura	50	3	60.16	98	0.61
Kumasi-Nkoranza	50	3	60.16	150	0.4
Kumasi-Wenchi	50	2.31	46.28	155	0.29
Accra-Tamale	50	4.04	80.98	654	0.12
Wenchi-Sunyani	130	6.94	53.39	97	0.56
Wenchi-Techiman	130	4.63	35.59	29	1.23
Wenchi-Accra	130	11.57	88.98	427	0.21

Source: World Bank (2012). *Note*: Prices converted to GHS with the market exchange rate of 1.74 GHS/USD

The postharvest losses of traders are substantially lower than the losses incurred when produce is kept on-farm since traders usually have at their disposal proper storage facilities and information about appropriate handling. On the other hand, traders have to take additional costs into account. First, storage in warehouses and the treatment of stored commodities are costly. In addition, traders incur the opportunity cost of capital. Last, traders usually bear the costs of transporting goods to their storage facilities and, after storage, to their customers; this includes the loading at point of departure. Exact estimates of transport and storage costs are difficult to obtain and also vary by orders of magnitude and in terms of quality (ZEF-ISSER Trader Survey 2013).

Table 23.1 presents the surveyed transport costs for frequently used destinations in Ghana in 2011. The unit cost of transporting over short distances is more expensive than transporting over standard trade routes between the urban centers Tamale, Kumasi, and Accra. Generally, the transport costs are significant when measured against the wholesale price of a mini bag of maize (50 kg; 30–35 GHS) and maxi bag (130 kg; 40–80 GHS) at that time. During the field survey, loading costs were reported to be 1 GHS for a maxi bag.

The per-unit storage costs cannot be easily calculated.[5] Therefore, in the interview, traders were asked how much they need to add to the purchase price in order not to make any losses (1) if they buy and immediately sell and (2) if they buy, store for 3 months, and then sell. In the latter case, the reported amount should yield the sole costs of storage without the trader's markup, while in the former case, the reported amount captures mainly the transport costs and also the fixed costs of administration and marketing. The results are reported in Table 23.2.

Transport and administrative costs reported are in gross accordance with the costs estimated by the World Bank (2012). Large firms in Accra and Kumasi reported the smallest amount of storage costs, which is unsurprising. Conversely, it is striking

[5] Due to the large share of fixed costs

Table 23.2 Transportation and storage costs from trader survey

Description	Reported costs
Large firms in urban centers	Storage costs: 12–18 GHS per ton
	Transport and admin costs: 25–30 GHS per ton
Traders in Brong-Ahafo	Storage costs: 1–1.5 GHS per 50 kg
	Transport and admin costs: 1–2 GHS per 50 kg
Traders in the Northern Region	Storage costs: 2–8 GHS per 100 kg
	Transport and admin costs: 5–12 GHS per 100 kg

Source: ZEF-ISSER Trader Survey (2013). *Note*: Differences across crops could not be observed, but the sample size for rice and soybeans was small; traders choose their preferred unit to report the costs

that the transport and administration costs are much higher than the storage costs for 3 months.[6] A comparable proportional relationship between the transport and storage costs can also be found in other studies (e.g., Angelucci 2012; EAT 2012; Angelucci et al. 2013). From our own survey, it can be deduced that the total operational costs constitute between 5 and 50 % of the purchase price.

In Ghana and elsewhere, it is generally observed that storage facilities are built to exploit economies of scale (Monterosso et al. 1985) or the proximity to processing companies in urban centers (EAT 2012). Benirschka and Binkley (1995) explain this phenomenon by the presence of opportunity costs that decrease with distance to the producing market. In consequence, market supply takes place in a sequential manner. Firms located far away from the market release their stocks only after those firms located closer to the market have fully released their stocks. This implies that as soon as grain supply in production regions is exhausted, grains will be transported back from urban centers to rural markets. In this way, transport costs are incurred twice: initially when grain is shipped from rural to urban areas after harvest and subsequently in the reverse direction during the hunger season (Barrett 1996).

Taking into account the high costs of transport, traders need to increase their sales price in order to break even. In light of this, seasonal price changes of around 50 % in selected years appear quite reasonable, and thus transport costs are a potential driver of the high seasonality of prices. Conversely, the costs of storage alone (excluding transportation costs) cannot account for the strong seasonality in prices.

23.3.4 Aggregated Results: Seasonality in Storage and Trade

The aggregated turnover of the survey respondents represents a significant portion of the total quantity marketed for rice and maize only.[7] The figures presented in Table 23.3 suggest that sorghum, millet, and soybeans pass through the hands of

[6]The figures should be interpreted cautiously with respect to the total size of the cost reported.

[7]Turnover is the total purchase of a trader within one marketing year.

Table 23.3 Stylized facts of grain markets and survey

	Maize	Rice	Sorghum/millet	Soya
National consumption 2013 (FAO GIEWS)	1,700,000	950,000	450,000	150,000
National production 2013 (FAO GIEWS)	1,800,000	300,000	470,000	150,000
Industrial use	20	n.a	n.a.	70
%—formally traded	50	>80	<20	85
No. of traders in sample	29(+2)	14(+8)	3	11
Turnover captured by the survey	94,000	377,000	–	7400

Note: Figures for soya are from MoFA (2013). The quantities for soybeans refer to raw commodities. Instead, soybean cake and oil are also imported. Estimates on industrial use are taken from EAT (2012). () indicate number of traders that purchase yellow maize and imported rice, respectively

wholesale traders less often than maize and rice. In addition, soybeans are used for human consumption only to a small extent. The figures indicate that processing firms, rather than traders, are largely involved in the storage of sorghum, millet, and soybeans. Therefore, the subsequent discussion is limited to maize and rice.

The sample cannot be considered representative with regard to the composition of the traders. Large wholesale companies are overrepresented, while the portion of traders with a capacity of a few dozen bags was relatively too small. The respondents of the survey purchase and sell commodities to different market actors. While the vast majority of the respondents buys their commodities from farmers or aggregators, about half of the respondents also purchases from other wholesale traders. With respect to sales, only seven respondents sell to consumers directly. In contrast, the vast majority interacts with other wholesalers, processing companies, and retail traders (ZEF-ISSER Trader Survey 2013).

The first indication of the seasonal variability of stocks is shown in Fig. 23.4, which illustrates the best time to stock in and to release stocks as specified by the survey respondents. For maize, stocking-in mostly takes place from August to September and November to January. This largely corresponds to the time of harvest, and thus the time of the year at which prices are lowest. Interestingly, some traders continue to build stocks throughout the year. In line with this, stock releases also occur throughout the year. Nevertheless, most traders prefer to sell their maize stocks from April to June in order to benefit from higher prices at that time. Results for rice are different. Stocks of imported rice exhibit less intra-annual variation apart from the fact that stocks are built before Christmas to satisfy the increasing demand. In contrast, traders stock up local rice between November and January with the intention to sell the local rice between March and June; this exemplifies the seasonality of rice prices.

Seasonal variation of actual stocks is deduced from the survey in the following way. First, stock levels of respondents are interpolated in order to fill gaps in the questionnaire. Second, estimated stock levels are aggregated by commodity. In doing so, large wholesale traders carry over-proportional weight, while stocks of smaller traders hardly change aggregated stock level. Figure 23.5 shows the

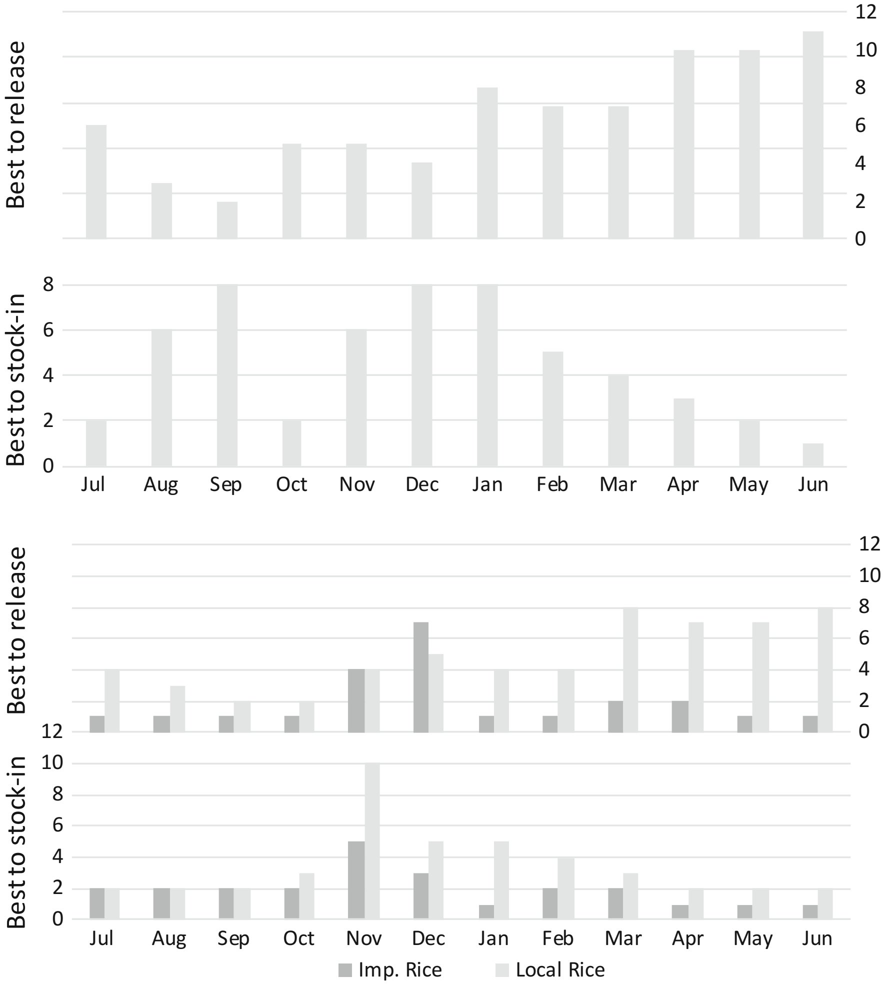

Fig. 23.4 Best time to stock in and stock out (no. of respondents). *Source*: ZEF-ISSER Trader Survey (2013)

seasonality of the observed stocks within the survey period. The estimates are in accordance with the preferred time of stocking-in and releasing stocks.

For maize, this is an increasing function until February/March. Maize stocks were accumulated in the course of the year and distributed toward the new harvest season. Over the survey period, maize stocks vary significantly between 10,000 and 45,000 tons. It seems that on-farm stocks dominate at the beginning of a marketing year, and trader stocks take over only in the last few months before the next harvest. This observation is different from what is known about traders' storage pattern in other countries, whereby stocks are usually highest after harvest and decline

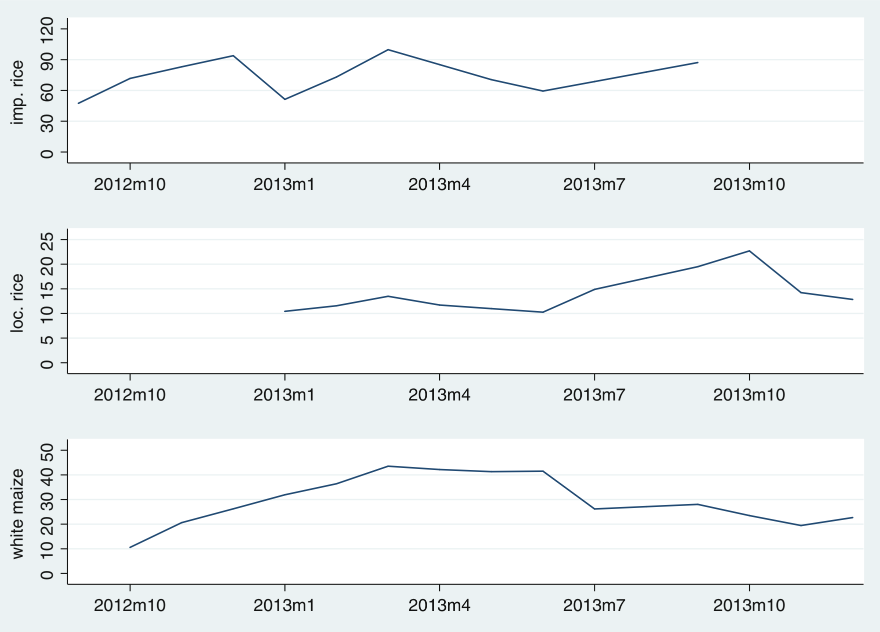

Fig. 23.5 Aggregated stock trend (in 1000 mt). *Source*: ZEF-ISSER Trader Survey (2013)

throughout the year.[8] From the qualitative interviews, we know that the safety stocks of maize processing companies are able to sustain their total production for 1–2 months. With the knowledge that 20 % of the total national consumption is used for industrial use, the level of stocks held by processors is estimated to be 40,000 mt. Similarly, we can estimate the amount of stocks held by retail traders from the daily consumption needs of the market.[9] Assuming that retailers hold enough stocks for 5 days, the national aggregate for retail trader stocks would be around 12,000 mt. Therefore, even if the survey respondents represented a large share of the market, wholesale traders would still carry the largest amount of maize stocks compared to other market participants.

Unlike maize, rice stocks did not show a similarly strong seasonality. Imported rice stocks were built up before Christmas and Easter and declined as a result of releases during festival time. Local rice stocks did not exhibit similar peaks around Christmas and Easter. On the contrary, the stock level reached its lowest point in June, and before that, rice was constantly accumulated. Similar to maize, local rice is processed, and millers are expected to also hold stocks throughout the year. The

[8]For example, see private stock data on South Africa by South African Grain Information Service (SAGIS).

[9]This is achieved by dividing the amount of maize marketed (850,000 mt) by 365 days.

same applies to both the imported and local rice stocks of retail trader. However, wholesale rice traders carry by far the largest amount of stocks throughout the whole year. Due to imports constituting a large share of the total rice stocks, rice stored by farmers is not important for rice.

23.3.5 Micro Results: Heterogeneity of Traders

Seasonal patterns of storage provide interesting insights into the market behavior on the national scale. The diversity of storage motives, as elaborated earlier, suggests heterogeneity in storage strategies among traders or groups of traders. In this section, we assess whether these differences are actually observable and discuss possible explanations. Individual stock-holding patterns by traders are shown in Figs. 23.6, 23.7, and 23.8.

A single common storage strategy cannot be observed among maize traders. By contrast, similarities in the behaviors of imported rice traders can be observed. None of the traders have entirely depleted their stocks in the course of the observation period. Furthermore, all traders tended to increase their stock level toward the end of 2013. Like maize, heterogeneous patterns can be observed in the stock level of local rice, apart from an increase in the stock level between September and December 2013, which is common for all traders. Overall, there are similarities between the

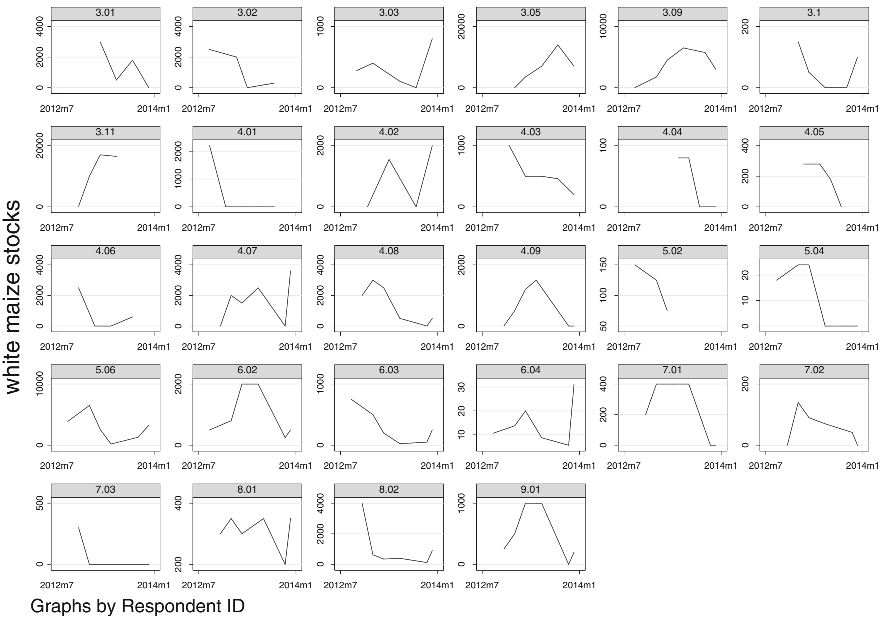

Fig. 23.6 Stocks by respondent (white maize). *Source*: ZEF-ISSER Trader Survey (2013)

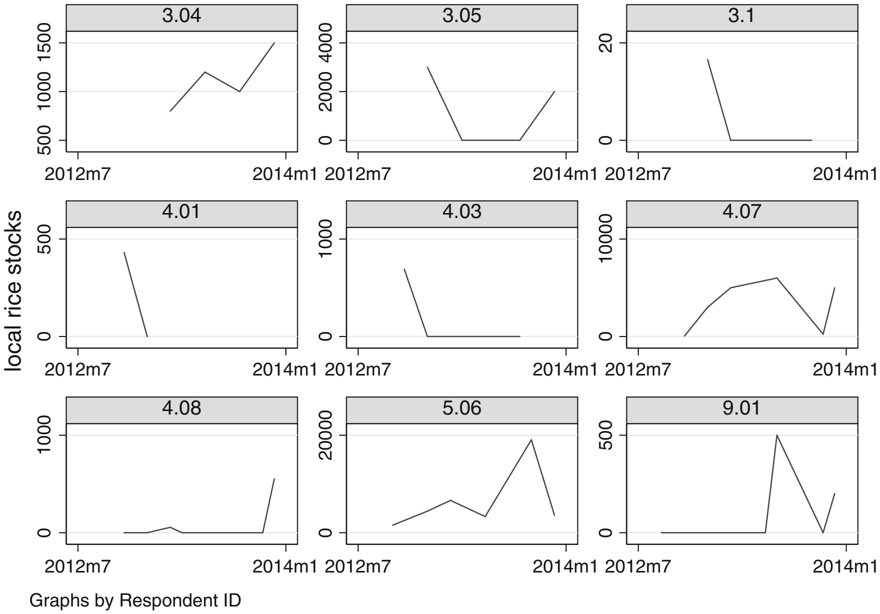

Fig. 23.7 Stocks by respondent (local rice). *Source*: ZEF-ISSER Trader Survey (2013)

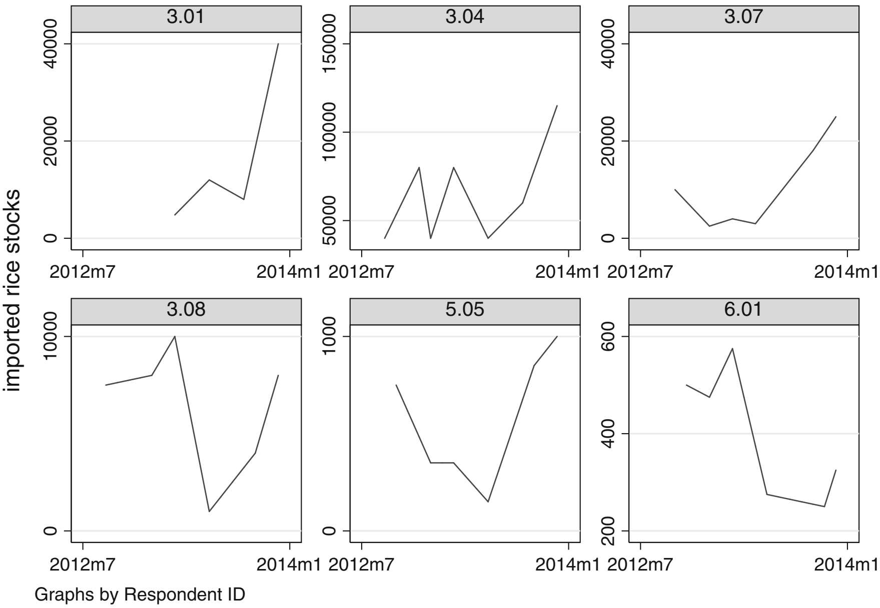

Fig. 23.8 Stocks by respondent (imported rice). *Source*: ZEF-ISSER Trader Survey (2013)

stocking trends of maize and local rice, while storage of imported rice seems to be determined by other factors.

From the discussion about storage motives, we recognize two distinct types of traders: aggregators, who accumulate predetermined amounts of stocks for delivery to their customers on a mutually agreed date; and speculators, who hold stocks to benefit from seasonal variation in prices. By contrast, we do not observe any stock trends which imply that stocks are held purely as safety stocks. This could be because the sample includes large wholesale traders but not retailers. However, it may also be because parts of the grain stocks, in particular of imported rice, are safety stocks that are held with the intention of guaranteeing continuous distribution.

To further analyze stocking patterns, we use a simple approach to differentiating stocking strategies. We distinguish between a U-shape and a reverse U-shape storage curve. A reverse U-shape curve represents the holding of stocks until mid 2013, which hints at a speculative strategy. Conversely, a U-shape curve implies purchases in late 2012 including more or less immediate sales and restocking in late 2013. The latter better describes the stocking pattern of an aggregator.[10]

Extrapolating on the stocking strategy from the seasonal variation in stocks only rests on fragile foundations. Instead, it is critical to understand what drives traders to follow a particular strategy that maximizes their profits or expected utility. In other words, what makes a trader a speculator and what makes them an aggregator or distributor. In this study, we will not go into detail on this, but we will briefly outline possible explanations, as illustrated in Fig. 23.9. Further research is necessary to validate the explanations.

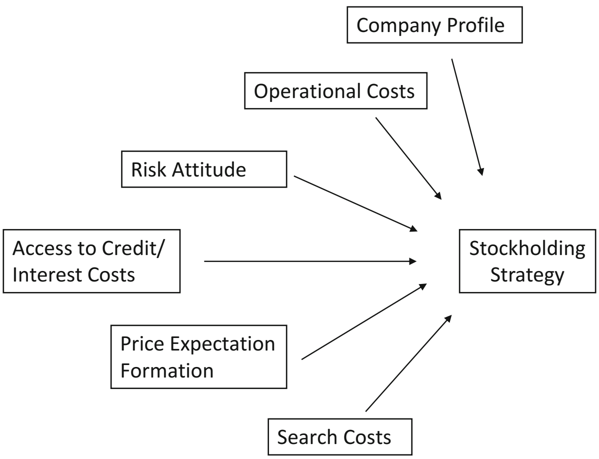

Fig. 23.9 Determinants of the stock-holding strategy. *Source*: Authors' illustration

[10]In total, we identify (U shape/reverse U shape) for maize (9/15), local rice (5/3), and soya (8/1).