Market information and smallholder farmer price expectations

Mekbib G Haile*
Centre for Development Research (ZEF), Bonn University, D-53113 Bonn, Germany. E-mail: mekhaile@uni-bonn.de

Matthias Kalkuhl
Centre for Development Research (ZEF), Bonn University, D-53113 Bonn, Germany. E-mail: Kalkuhl@mcc-berlin.net

Muhammed A Usman
Centre for Development Research (ZEF), Bonn University, D-53113 Bonn, Germany. E-mail: muha2005@yahoo.com

*Corresponding author

Abstract

Price expectation plays an indispensable role in production, marketing and the agricultural technology adoption decisions of farmers. Using household survey data, this paper analyses the price expectations of farmers growing cereals and horse beans in Ethiopia. Our findings show that current and past output prices in local markets, central wholesale prices and seasonal rainfall are strongly correlated with smallholders' price expectations. Reliable information on these variables assists farmers to form better price expectations, thereby improving their production decisions. This supports the recent developments in using information and communication technologies (ICTs) and market information systems (MIS) to convey market and weather information to farmers.

Key words: Smallholder farmer, price expectations, access to information, agriculture, Ethiopia

1. Introduction

Economic agents use different information when making decisions on their economic activities. Among many, past trends, outcomes in related markets, media reports, weather and published forecasts are some of the information that agents use in their resource-allocation decisions (Just & Rausser 1981). The intrinsic feature of agriculture, which is a time lag between production decision and output realisation, makes the role that information plays for agricultural producers indispensable. Besides, agricultural production is inherently stochastic due to weather shocks, pest infestations and other shocks that affect the general market supply condition and therefore prices. Farmers rely on their price expectations to make planting decisions. Farmers therefore invest in the gathering and processing of price and other information, which they believe is a good predictor of prices at harvesting time. Identifying the information set that smallholders use, and modelling how this information set is utilised in their production decisions, hence is important.

The information set and the relevance of each of the constituting elements vary widely across producers, depending on their access to information, education level, geographical context and their ability to process information (Chavas 2000). This paper focuses on smallholders in rural Ethiopia, where published price forecasts are non-existent and the literacy rate is quite low. Nevertheless, as any other agricultural producer, these rural households have their own information set to form price expectations on which they base their agricultural production decisions. Smallholder farmers are dynamic actors who respond to economic incentives and risks that they perceive in their environment (Von Braun 2004). Studies have indicated that smallholder farmers, despite being poor, are efficient in their resource utilisation (Schultz 1964). This study therefore attempts to

understand the mechanisms through which subsistence farmers form price expectations. More specifically, this study identifies information sources that are most relevant in the formation of price expectation by Ethiopian smallholders. The findings can guide policy makers in terms of prioritising investments in information provision to farmers. The information that farmers use in their price expectation formation also assists in providing a signal for domestic production changes in the coming harvest season (to the extent that farmers base their farming decisions on prices). This, in turn, helps as an early indicator of the food security situation in the country.

Several approaches have been applied to model the expectations of economic agents. Naïve, adaptive and rational expectations are the most commonly applied approaches in agricultural markets. The naïve expectation hypothesis (Ezekiel 1938) assumes that futures prices will be, on average, the same as the latest observed prices. Thus, a naïve farmer forms his expectation of futures prices based on current prices. The adaptive expectation hypothesis (Nerlove 1956), on the other hand, assumes that price expectations evolve over time, such that farmers make adjustments in their expectations depending on past errors. The other expectation hypothesis, which has been dominant since the 1960s, is the rational expectation hypothesis (Muth 1961). The rational expectation hypothesis, in its strong sense, assumes that expectations are consistent with the underlying market structure and that economic agents make efficient use of all available information for their price expectation formations. This hypothesis is based on the assumption that agents know the true data-generating process (Evans & Ramey 2006). Futures prices have also been used as proxies for price expectations (Gardner 1976).

Since obtaining and processing information is costly, it is less likely that producers make use of all available information to form their price expectations (Orazem & Miranowski 1986). This is particularly so in the context of subsistent smallholder farmers with limited access to information and capital. Consequently, recent research has focused on modelling supply response using a quasi-rational price expectation, which forecasts prices from a reduced-form dynamic regression equation (Holt & McKenzie 2003). The quasi-rational expectation hypothesis has more realistic assumptions about producers' information sets and their data processing knowledge. Empirical applications also show the relevance of this approach in modelling supply response (Nerlove & Fornani 1998; Holt & McKenzie 2003).

This study therefore identifies the relevant variables that constitute the information set of a typical smallholder farmer in his price expectation formations. The importance of each of the elements in the information set is investigated. Only a few previous studies have analysed farmers' price expectations using primary data (Fisher & Tanner 1978; Kenyon 2001). This study provides some new insight into how smallholder farmers actually form their price expectations in the light of the availability of several theoretical models of price expectation formation.

2. Context and data

By and large, agriculture in Ethiopia is dominated by smallholder farming.[1] Smallholder agriculture contributes about 95% of the total agricultural production and 85% of total area under cultivation in the country (CSA 2010; Salami *et al*. 2010). Smallholder farmers grow various crops, both for own consumption and for market supply. Cereals are the most commonly produced crops by smallholders in Ethiopia, covering roughly 80% and 85% of the total grain crop area and production respectively (CSA 2012). *Teff*,[2] maize, sorghum, wheat and barley are the dominant cereal crops cultivated in a wide range of agro-ecological zones in the country. Pulses and oilseeds are the other

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[1] A smallholder in our context is defined as a farming household with a landholding of less than two hectares.
[2] *Teff* is a fine grain that grows predominantly in Ethiopia and is an important staple food in the country.

crops cultivated by smallholder farmers, whereas smallholders' participation in the horticulture sector is quite limited.

Poor productivity (because of lack of access to information, the market and credit, and low adoption of modern agricultural technology) is a long-standing challenge of smallholders in Ethiopia. For instance, in the 2009/2010 main cropping season, less than half of the farmers applied chemical fertilisers and only 12% of them sowed improved seeds (Abebaw & Haile 2013). A critical feature of Ethiopian smallholding agriculture is that it is predominantly rain-fed. As a result, the amount, timing and variability of rainfall are crucial for good agricultural productivity in the country. Rainfall is the commonly observed exogenous phenomenon that represents one of the main sources of information about future production in Ethiopia (Osborne 2004).

Data for this study came from a primary survey of rural smallholders in seven villages from four different districts of Ethiopia, namely Kersa, Shashemene, Ada'a and Debre Birhan Zuria. Smallholders in these areas produce both staple crops – typically wheat, barley, maize, sorghum and horse beans, and cash crops – like *chat*[3] and potatoes. The survey was conducted in April/May 2013 on a total of 415 households that were randomly selected from each village using stratification techniques. The households in our sample were those selected for the bigger Ethiopian rural household survey (ERHS), and detailed information on the sampling techniques can be found in Dercon and Hoddinott (2004).The survey was done immediately before or at the onset of planting for the main 'meher' season. This helped us to obtain sound information on planting-time prices. Furthermore, the dataset provides detailed information on household demographics, asset holdings, production and consumption, purchases and sales, seasonal prices and information sources, among others. Following the liberalisation of markets in Ethiopia in the early 1990s, prices have not only served as incentives to produce more, but they have also become less predictable. Consequently, recent volatile food prices have posed additional challenges for farmers in their production decisions. Information regarding input and output price developments, weather conditions and input availability therefore is crucial for a farmer to make a better production decision.

Farmers form their price expectations based on their access to information. We asked the respondents two similar but subtly different questions regarding their sources of price information. First, we wanted to know about farmers' major sources of price information. Second, we asked them a more specific question with regard to what information they observes to forecast the harvesting time price of their crop choice for cultivation. Figure 1 shows the major responses of the households. There are three major sources of price information for rural households in Ethiopia. Most of the smallholder farmers (54%) visit close-by markets to sell or buy products, and thereby obtain information about prices of their commodities of interest. About 45% of the respondents obtained price information from their fellow farmers. Although about two-third of the households own either a radio (57%) or a television set (8%), it is only a quarter of the rural households that report radio or television as sources of output price information. This may be because of a lack of awareness of the exact times when price information is transmitted. The descriptive statistics also indicate that the Ethiopian commodity exchange (ECX) has not done enough to reach out to rural smallholder farmers with price information.[4]

About half of the smallholder farmers formed their harvesting time price expectations based on currently available price information (Figure 1). About a fifth of the respondents considered past prices during the harvesting period in their price expectation formation. This may suggest that many households formulate their price expectations in line with the adaptive or naïve price expectation

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[3] *Chat* is a perennial cash crop and a mild stimulant that is commonly used in the southern and eastern parts of Ethiopia.
[4] The ECX was established in 2008 as a partnership of market actors, members of the Exchange, and the government. It is a marketing system that, among other things, aims to disseminate real-time market information to all market players.

formation hypothesis. This is consistent with a finding by Chavas (2000), who also found 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, are reported as relevant information in the process of price expectation formation by the smallholder farmers.
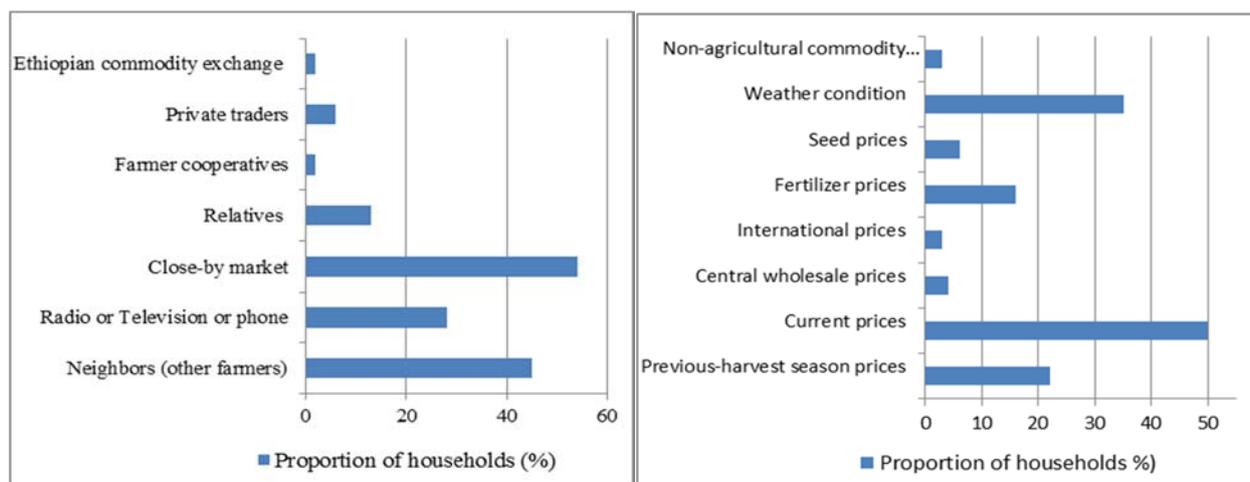
Figure 1: Primary source of price information (left) and relevant information for price expectation formation of smallholders (right)

Figure 2 depicts the ratio of the current year's harvesting season prices to the same season's prices in the previous year (red line) and to planting time prices in the current year (blue line). The price ratios illustrate how accurate planting prices or previous harvesting period prices can predict upcoming harvesting season prices. These are indicative of how good a naïve farmer, who bases price expectation on either or both of these prices, can predict upcoming harvest-period prices. Regarding *teff*, wheat and maize, the historical price series show that planting season prices are more informative to predict harvesting season prices than the previous harvesting season prices. However, neither price series seem to be a good predictor for sorghum.

Except for sorghum, Figure 2 shows that the significant rise in the nominal harvesting period prices of the crops (over the 12 months between December 2007 and December 2008) was already apparent in the price changes between the corresponding planting months. This is reflected in the close to unity ratios of harvesting to respective planting season prices. For instance, the harvest-period *teff* price nearly doubled between 2007 and 2008, whereas that of maize increased by about 80% over the same period. The corresponding planting period prices more than doubled between these seasons: this is shown by the respective price ratios that are less than unity. The large price variations between two consecutive harvesting seasons (which are as high as 50% in a few cases) hint that last year's harvesting season prices might be poor predictors of upcoming harvesting season prices. Consequently, planting time output prices may be taken as more relevant price information for price expectation formation than previous harvesting period prices.

Secondary data for our analyses, including central wholesale prices and international prices, were obtained from the FAO GIWS and World Bank price databases respectively. Historical rainfall data were obtained from the national meteorology agency (MNA) of Ethiopia.
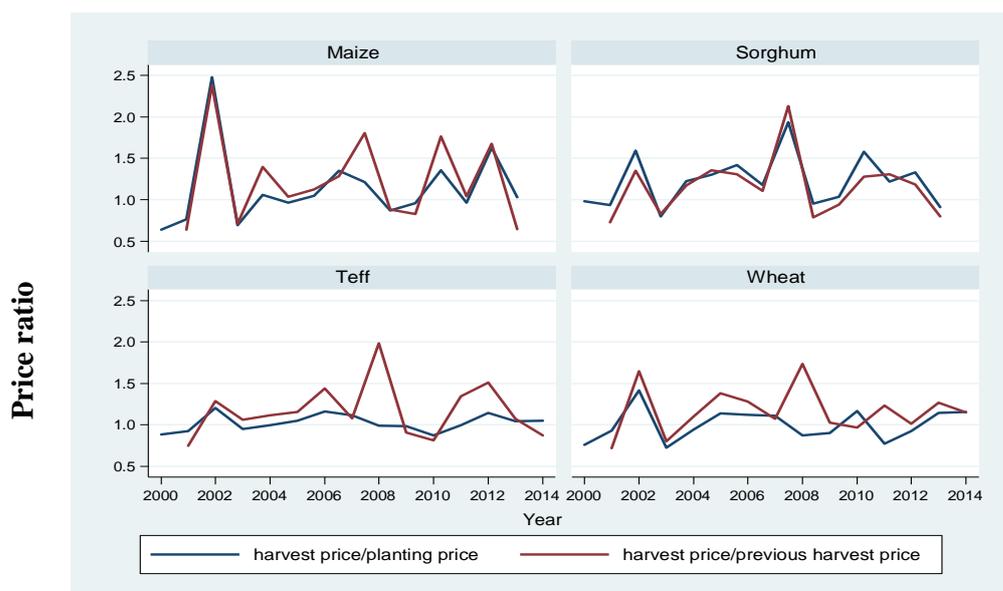
Figure 2. Wholesale prices of major cereals in the planting and harvesting months, 2000–2013

3. Price expectation formation

3.1 Conceptual framework

A basic economic supply model explaining the production of a certain crop is specified as a function of its own and competing crops' harvesting time prices and other exogenous factors. Nevertheless, the harvesting time prices are not realised during the time of input allocation, and producers need to form their own price expectations. Thus, a simple supply-response model of a given crop at time t can be specified as:

$$Q_t = \beta_1 + \beta_2 p_t^e + \beta_3 Z_t + u_t \tag{1}$$

where Q_t is the desired output or acreage in period t, p_t^e is a vector of expected prices of the crop under consideration and of other, competing crops, Z_t is a set of other exogenous variables, and u_t accounts for unobserved random factors affecting crop production. Hence, there is an underlying price expectation that economic agents form and of which the supply response modeller should draw up a hypothesis.

There is little agreement among applied researchers regarding any *a priori* superior specification for price expectation (Shideed & White 1989). Smallholder price expectation depends on several factors: Figure 3 illustrates some of the factors that potentially constitute the relevant information set in the context of smallholder farmers in a typical developing country. The smallholder farmer gathers information from several sources about, among others, previous and current output prices, input prices and weather conditions. The farmer then processes the gathered information and makes his expectation about the likely price of his crop choice during the next harvesting period. This data processing stage and the degree of accuracy in forecasting the harvesting time prices, however, depend on the asset and household characteristics, level of education, income level and risk perception of the smallholder farmer. Conditional on the respective expected prices, the smallholder decides how much fertiliser, labour, acreage and land management to allocate to each crop.
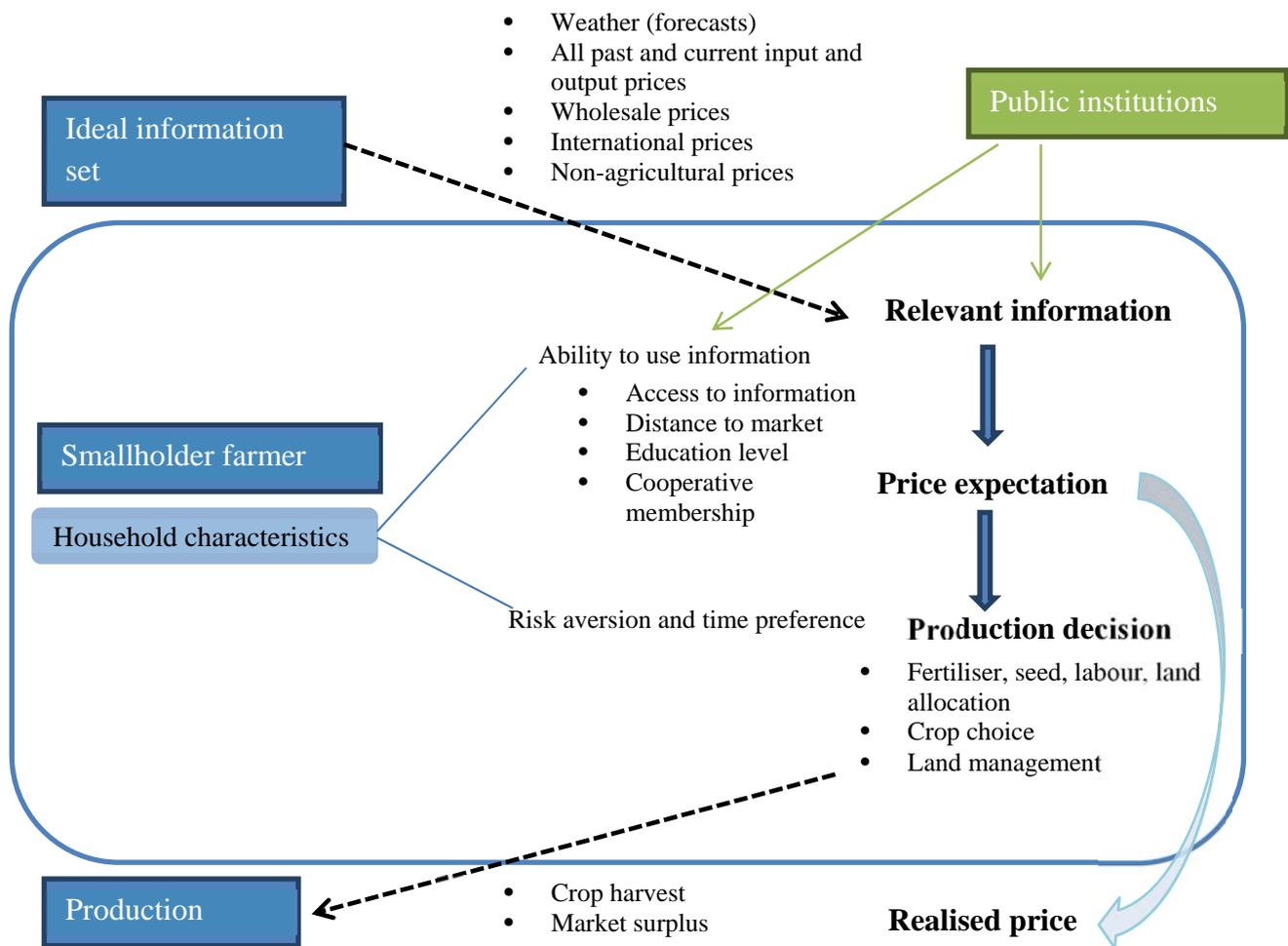
Figure 3. Conceptual framework, own illustration

In general, price expectation in the supply model in equation (1) can be specified as:

$$p_t^e = f\left(p_t, p_{t-1}, \dots, p_{t-p}, w_t, w_{t-1}, \dots w_{t-p}, r_t, Z_t\right) \tag{2}$$

where $p_t, p_{t-1}, \dots, p_{t-p}$ and $w_t, w_{t-1}, \dots w_{t-p}$ refer to current and previous output and input prices, r_t refers to actual sowing time and expected growing time rainfall quantities, and Z_t denotes other exogenous variables that potentially could explain expectations. The above function is general and it allows different price expectation hypotheses to be used, depending on what information we include in the function. If expectations are assumed to be formulated in line with the rational expectation hypothesis, an autoregressive moving average model of output prices should be estimated after substituting the price expectations function in the supply model. A quasi-rational expectation hypothesis, on the other hand, generates a one-step price forecast and uses these prices as data in the supply response model (Shideed & White 2989). Similarly, the naïve expectation model equates the expected price with the market price in the previous year, whereas in the futures price expectation model the price associated with a futures contract at harvest is used to proxy price expectations.

For instance, as it is typical in the literature, a quasi-rational expectation can be formulated using an error-correction time series model. Suppose x_{t-1} represents a set of exogenous variables that smallholders use in predicting their output prices, p_t^e, a quasi-rational price expectation hypothesis can be defined in the form of an error-correction model specification:

$$\Delta p_t^e = \alpha \Delta x_{t-1} + \rho z_{p,t-1} + \varepsilon_t \tag{3}$$

where $\rho z_{p,t-1}$ is the long-run relationship between the dependent variable and the explanatory variables, with ρ as the co-integrating term. After estimating Equation (3) with ordinary least squares, the fitted values can be used to represent the economic agents' price expectation in Equation (1) above.

3.2 Empirical model

Most of the theoretical models and empirical applications of price expectation formation are in the context of a time series analysis (Nerlove & Fornani 1998; Holt & McKenzie 2003). This is because the harvesting period prices are not known and one needs to forecast or predict them based on past price realisations. Hence, the researcher hypothesises a model that he or she thinks best represents the agent's expectation formation. In this study, we obtained the expected prices of smallholder farmers from the household survey data. Thus, we did not need to forecast a price that was supposed to represent the agent's expectation. Instead, we identified the factors that enable the agent to come up with the reported expected price.

There are five major cereals, namely *teff*, wheat, maize, sorghum and barley, and a common leguminous crop in the context of Ethiopia, horse beans, for which we gathered expected price information from smallholders. In general, the expected price of the ith household for a given crop c at sowing time ($t = s$) can be specified as:

$$p_{ic,s}^e = \alpha_0 + \sum_{t=h,s} \alpha_t \, p_{ic,t} + \sum_{t=h,s} \beta_t \, p_{c,t}^{cw} + \sum_{t=h,s} \gamma_t \, p_{c,t}^I + \theta w_{i,s} + \sum_{t=s,g} \eta_t \, r_{ic,t} + v_{ic,s} \tag{4}$$

where h, s and g refer to the previous harvesting and the current sowing and growing seasons respectively. The second term on the right, for instance, refers to previous harvesting and current planting period output prices, both obtained from the survey. The superscripts cw and I denote central market wholesale prices and international prices respectively. $w_{i,s}$ refers to variable input expenditure, which consists of expenses for fertiliser, pesticides, hired labour, purchased seed and renting oxen. Because input expenditure is usually known to farmers at planting time, we only considered expenditure during planting. Rainfall, both at planting and in the growing periods ($r_{ic,t}$), also affects price expectations. Finally, $\alpha, \beta, \gamma, \theta$ and η are parameters to be estimated, and $v_{ic,s}$ is the error term.

The dependent variable, $p_{ic,s}^e$, was obtained from a survey that asked farmers to report their expected prices (at sowing time) for each crop for the next harvesting season. Moreover, the farmers reported regarding their knowledge of crop prices for the previous harvesting season and for the current sowing period, referred to as $p_{ic,h}$ and $p_{ic,s}$ in Equation (4). We also constructed harvesting and sowing period crop prices using wholesale prices from the Addis Ababa market, $p_{c,h}^{cw}$ and $p_{c,s}^{cw}$, and international output prices, $p_{c,h}^I$ and $p_{c,s}^I$. The wholesale and international prices obviously vary across crops. Moreover, these seasonal prices have some degree of variation across farmers, depending on the planting and harvesting seasons of the crops that farmers grow. Only 2% of the smallholders reported international prices as relevant information for their expectation formations. Because some crops (e.g. *teff*) are not traded in the international market, we used only the domestic wholesale prices in our empirical model. This is also important to reduce any multicollinearity problem in the data that may be a concern for our empirical estimation.

The rainfall variables, $r_{ic,s}$ and $r_{ic,g}$, refer to rainfall amounts in the sowing and growing periods in millimetres. While the former is the rainfall amount observed, the latter refers to smallholders' rainfall expectations for the upcoming growing months of each crop. Thus, $r_{ic,s}$ is the amount of rainfall recorded at nearby meteorological stations in the sowing period for each crop. The average growing period rainfall over the previous five years was used as a proxy for farmers' rainfall expectations for the coming growing season. The rainfall variables vary across households, since rainfall varies across the four diverse geographical study areas. Besides, we multiplied the rainfall at sowing time by the dummy of rainfall included in the questionnaire, in which smallholders were asked if rainfall at sowing time was enough and on time. This is important because it is not only the village-level rainfall amount that matters, but also its timing and its amount with respect to each crop requirement. Furthermore, the rainfall variables vary across crops, depending on the planting and growing months of each crop.

Table 1 provides the summary statistics of the variables that were used in the empirical model. One can see that the planting period prices are, on average, higher than the previous harvesting season prices for all crops. This is a typical feature of seasonality in agricultural markets. Most smallholders have little storage capacity. They sell their crops immediately after harvest, when prices are low. This is consistent with the anecdotal evidence that liquidity-constrained smallholder farmers generally tend to sell their crops immediately after the harvesting season, with studies that indicate similar patterns for Ethiopian farmers (Osborne 2005).

Farmers' anticipated prices were, on average, in between the previous harvesting and current sowing prices for nearly all crops. This finding remains unchanged even after adjusting for inflation with the average national consumer price indices (CPI) in the respective periods. Barley is mainly grown in the Debre Birhan Zuria district, where there is a high degree of land degradation. Smallholders in this district spend the most on variable inputs, mainly on fertiliser. Barley, *teff* and wheat have relatively higher fertiliser and other variable input requirements. The rainfall amount typically is lower during the sowing period compared to the growing period for all crops.

We pooled the data across the six crops and estimated Equation (4) using pooled ordinary least squares (OLS). However, unobserved heterogeneity across households, such as ability to gather and process data, could affect price expectation, which potentially causes an endogeneity problem in the OLS estimation. A good proxy for such household heterogeneity can address this problem. We computed the price forecasting errors of each smallholder farmer by taking the deviation of the farmer's expected price from the respective realised harvesting period crop prices.[5] This price forecasting or prediction error of smallholders can serve as a proxy for some of the unobserved household characteristics, such as their abilities to obtain and process information. Yet this proxy might not capture all relevant unobserved household characteristics. We expected that unobserved farmer characteristics would remain unchanged, regardless of which crop a farmer grows. An obvious remedy would be to collect longitudinal data for the same farmers for multiple periods and include farmer-fixed effects in the model. Our dataset was based on a single-period survey, but it contained information on the same farmer for three different periods, namely previous harvesting, current sowing, and future harvesting periods, and for a maximum of six crops. We can get rid of such unobserved farmer heterogeneity in a fashion similar to the fixed-effects (FE) panel data framework. To this end, we framed our dataset such that it has a panel structure, where the same farmer reported his expected prices for multiple crops. We refer to this approach as an *FE-like* approach to distinguish it from the usual FE model. The FE model removes time-invariant farmer heterogeneity, whereas the *FE-like* model enables us to get rid of *crop-invariant* unobserved farmer

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[5] Because the calculation of prediction errors requires knowing the respective realised harvesting period crop prices, we collected this information from our study villages at the end of the harvesting period.

characteristics. While the FE analysis requires data to vary over time, the *FE-like* analysis requires data variability across crops. All price variables obviously vary across crops, as do the rainfall variables because of differences in cropping seasons.

Table 1: Descriptive statistics of the variables used in the expectation model, by crop

Crop	*Teff*	Wheat	Maize	Sorghum	Barley	Horse beans
Variable	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*
Expected price	1 441 (307)	690 (135)	575 (131)	707 (168)	568 (125)	698 (158)
Previous harvest price	1 320 (228)	652 (102)	525 (86)	644 (117)	553 (100)	670 (136)
Sowing price	1 516 (167)	726 (95)	586 (66)	704 (125)	622 (85)	726 (144)
Sowing rainfall (mm)	128 (34)	128 (36)	82 (35)	82 (36)	128 (34)	128 (34)
Growing rainfall (mm)	171 (77)	171 (87)	193 (78)	193 (76)	171 (77)	211 (106)
Input expenditure (Birr)	1 040 (1 793)	1 008 (1 030)	186 (312)	283 (366)	2 017 (1 623)	381 (615)
Previous harvest wholesale price	1 309 (0)	667 (0)	461 (0)	942 (0)	500 (0)	1 100 (0)
Sowing wholesale price	1 343 (0)	738 (0)	474 (0)	839 (0)	700 (0)	1000 (0)
Previous harvest world price	–	643 (0)	573 (0)	521 (0)	451 (0)	–
Sowing world price	–	570 (0)	542 (0)	516 (0)	431 (0)	–
Prediction error (%)[6]	20 (9)	19 (9)	19 (10)	19 (11)	20 (10)	19 (01)
Number of observations	172	313	213	133	188	168

Note: All prices are in Ethiopian Birr per 100 kg.[7] The international prices are averages of sowing and harvesting month prices.
Source: Authors' own calculation using survey data

We conducted the Hausman test to check for the exogeneity of the fixed effects. The test result indicates that the farmer fixed effects were correlated with the covariates in the model. This suggests that parameter estimates will be biased if the fixed effects are left in the error term, as is done in the random effects model. Thus, we estimated farmers' price expectations using the *FE-like* regression model.

4. Results and discussion

Table 2 presents the econometric results for the expectation model in equation (4). The first two columns report results from OLS regressions for the sake of comparison. In the second column, we use price prediction errors of smallholders as proxies for the unobserved farmer heterogeneity described above. Because of the potential endogeneity problem in the expectation model, and since the proxy may not fully capture the endogenous variables, we preferred estimations from the *FE-like* model. The results of the expectation model from our preferred estimation technique show that the statistically significant control variables have an *a priori* expected sign, which is consistent with

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[6] This is the relative deviation in farmers' expected prices from the actual crop prices that were observed in the local markets at harvest time for which expectations were formed.

[7] Average official exchange rates during the harvesting and planting periods were 18.07 and 18.42 Birr per US Dollar respectively.

standard economic theory. The values of the R-squared in Table 2 are also informative of the good fit of the estimated models.

Focusing on results from the *FE-like* model, farmers tended to have a higher price expectation for the next harvesting period if they observed higher local market output prices in the previous harvesting and current sowing periods. More specifically, a 100 Birr increase in each of these output prices [in nominal terms] was associated with a 50 Birr higher expected price by a typical farmer, *ceteris paribus*. Similarly, farmers tended to have higher price expectations if they observed higher wholesale prices at the central market in the previous harvesting period. However, the smallholders seemed to care little about the wholesale prices in the capital market at the time of sowing and, if at all, it had a negative correlation. This may be because the farmers in our sample were predominantly subsistent and did not have surplus output that lasted until the next sowing period. They took their crops to markets typically after the harvesting period to pay loans, which they often took to purchase fertilizer and other inputs at planting time. This finding supplements the descriptive statistic results and it may be explained by the liquidity-constrained nature of farmers in developing countries (Osborne 2005). Although about a third of the smallholder farmers used chemical fertiliser for at least one of their cultivated crops, input expenditures did not have statistically significant correlation with farmers' price expectations.

Table 2: Expectation model results

Dependent variable: Farmer price expectation			
	OLS	OLS proxy	*FE-like*
Previous harvest price (local)	0.42***	0.44***	0.46***
	(0.06)	(0.06)	(0.07)
Sowing price (local)	0.58***	0.56***	0.49***
	(0.05)	(0.06)	(0.06)
Sowing rainfall	0.36*	0.33	-0.29
	(0.15)	(0.2)	(0.89)
(Expected) growing rainfall	-0.02	-0.03	-0.62**
	(0.06)	(0.08)	(0.28)
Previous harvest price (wholesale)	0.12**	0.14**	0.09*
	(0.05	(0.05)	(0.05
Sowing price (wholesale)	-0.13	-0.15*	-0.05
	(0.07)	(0.07)	(0.06)
Input expenditure	-0.003	-0.001	-0.001
	(0)	(0)	(0)
Prediction error		2.72***	
		(0.78)	
Intercept	1.36	-47.54*	84.10
	(18.13)	(21.66)	(51.64)
Adjusted R-square	0.80	0.81	0.89
AIC	15 283	15 246	14 036
BIC	15 323	15 292	14 072
N	1 187	1 187	1 187

Notes: Robust standard errors adjusted for household clusters are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Rainfall is another important factor that shapes smallholders' price expectations. Both sowing and growing period rainfall have an expected negative sign, implying that farmers lower their expected prices following good rainfall conditions. Since the rainfall variable is adjusted both by its timing and amount, it reflects the appropriate rainfall for a better production in that particular season.

We did alternative specifications of our preferred model. To understand whether previous harvesting or current sowing period local prices are more relevant in the price expectation formations of smallholders, we excluded either of these variables in the *FE-like* regression (**Table**

3). Similarly, we alternatively included last year's harvesting and current planting season wholesale prices to assess which price is more important as information for forecasting future prices (**Table 4**). These alternative specifications are important for at least two reasons. First, these price variables are correlated, and using only one could suffice. Second, it is costly for smallholder farmers to search for price information, and they choose to minimise this cost. These alternative model specifications hint at which price series is more relevant and hence is more rational to search information about. We used the adjusted R-square and the respective Akaike's information criterion (AIC) and Bayesian information criterion (BIC) for our model choice.

Table 3: Alternative models of price expectation formation (current sowing prices versus last year's harvest prices, local prices)

Dependent variable: Farmer price expectation					
	(1)	(2)	(3)	(4)	(5)
Previous harvest price (local)		0.87***		1.04***	0.48***
		(0.05)		(0.03)	(0.07)
Sowing price (local)	0.82***		0.91***		0.51***
	(0.03)		(0.02)		(0.06)
Sowing rainfall	0.24	-0.49	0.64	-0.32	
	(1.04)	(1.04)	(1.06)	(1.01)	
(Expected) growing rainfall	-0.92***	-1.35***	0.08	-0.20	
	(0.3)	(0.33)	(0.23)	(0.23)	
Previous harvest price (wholesale)	0.09*	0.01			
	(0.06)	(0.06)			
Sowing price (wholesale)	0.03	0.20**			
	(0.07)	(0.09)			
Input expenditure	-0.004	-0.003	-0.01	0	
	(0.01)	(0.01)	(0.01)	(0.01)	
Intercept	106.62*	135.85**	8.93	22.83	9.90
	(59.83)	(61.01)	(56.28)	(19.42)	(16.25)
Adjusted R-square	0.87	0.87	0.87	0.86	0.89
AIC	14 241	14 301	14 269	14 375	14 038
BIC	14 271	14 332	14 290	14 395	14 048
N	1 187	1 187	1 187	1 187	1 187

Notes: Robust standard errors adjusted for household clusters are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Both the last year's and the contemporaneous price variables are important in shaping the price expectation formations of smallholder farmers (**Table 3**). Including information on both price variables explains the variation in price expectations of smallholders better than including either price alone. If only one price series has to be included, local sowing price has a better explanatory power than harvesting price (larger adjusted R-square, smaller AIC and BIC in column 3 than in 4). In other words, a farmer who has limited capital to search for information about both prices would obtain information on current sowing prices rather than last year's harvesting season prices. This could be explained by the proximity of current sowing season prices to the next harvesting period. It is also the price information that is fresh in the farmers' memory. Similarly, planting season central wholesale prices do also have larger association with farmers' price expectations than last year's harvesting period prices (**Table 4**).

Information sources that farmers use to form price expectations may vary across farmers based on variations in education and farm size. To test this presumption, we alternatively included interaction variables of our independent variables with education and farm size in the *FE-like* specification. These results, which are reported in the appendix, suggest that the mechanism through which farmers form their price expectations and therefore the importance of information sources remain

unchanged, regardless of level of education or farm size. These variables are not jointly statistically significant.

Table 4: Alternative models of price expectation formation (current sowing prices versus last year's harvest prices, central wholesale prices)

Dependent variable: Farmer price expectation					
	(6)	(7)	(8)	(9)	(10)
Previous harvest price (local)	0.49***	0.49***			
	(0.06)	(0.06)			
Sowing price (local)	0.46***	0.46***			
	(0.07)	(0.07)			
Sowing rainfall	-0.07	-0.21	0.71	-0.94	
	(0.87)	(0.89)	(1.91)	(1.96)	
(Expected) growing rainfall	-0.34	-0.56**	-5.40***	-7.99***	
	(0.24)	(0.27)	(0.33)	(0.40)	
Previous harvest price (wholesale)		0.06***		0.86***	-0.55***
		(0.02)		(0.03)	(0.05)
Sowing price (wholesale)	0.06**		0.99***		1.55***
	(0.02)		(0.03)		(0.06)
Input expenditure	-0.004	-0.002	-0.02**	0.01**	
	(0.04)	(0.004)	(0.01)	(0.01)	
Intercept	38.21	69.13	494.67***	948.16***	-71.51***
	(45.73)	(47.85)	(88.42)	(94.87)	(21.99)
Adjusted R-square	0.89	0.89	0.70	0.65	0.67
AIC	14 039	14 035	15 243	15 435	15 359
BIC	14 069	14 066	15 263	15 456	15 369
N	1 187	1 187	1 187	1 187	1 187

Notes: Robust standard errors adjusted for household clusters are in parentheses. ***, ** and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

The empirical results should be viewed with some caution: our analysis does not entail a causal statement, but correlation of the dependent variables with smallholders' price expectations. For instance, the positive coefficient of local sowing price in Table 2 (0.49) may not be argued as a causal effect such that a 1 Birr higher local sowing price causes a 50 cents increase in the average farmer's price expectation. It should rather be interpreted as that local sowing prices of a crop are positively associated with farmers' price expectations for the upcoming harvesting season.

5. Conclusions

Price expectations play a crucial role in the production, marketing and agricultural technology adoption decisions of farmers. Producers invest in acquiring and processing price and other information, which they believe will improve their price expectations. This process is costly for the individual farmer. Additionally, there is a certain level of externality because the information a farmer obtains is a partially non-excludable public good that other farmers may have access to without paying. Accordingly, it might be necessary for the government to provide market information as a public good through organised market information systems. This requires identifying the most relevant information sources for farmers and the mechanisms through which smallholders from price expectations.

Using a primary survey dataset that elicits smallholders' price expectations for the coming harvesting period, this study identified the relevant information set that farmers use in their expectation formulations. The empirical findings show that information regarding current and past output prices in nearby grain markets, central wholesale prices and seasonal rainfall patterns shape smallholders' price expectations. There are a few institutions that potentially could improve

smallholders' access to market information in Ethiopia. The long-lasting Ethiopian Grain Trade Enterprise (EGTE), as well as the recently launched Ethiopian Commodity Exchange (ECX) and the Agricultural Transformation Agency (ATA), aim at improving agricultural productivity and marketing efficiency in Ethiopia. These institutions can assist farmers by providing and disseminating accurate and timely central wholesale prices. In coordination with the National Meteorology Agency (MNA), they could also provide better early warning information regarding seasonal weather conditions.

Local prices (nearby grain market prices) generally constitute a better information set for farmers' price expectations than central wholesale prices. Smallholder price expectations are most highly correlated with current sowing and previous harvesting period prices in the local market. Comparing the results for sowing and harvesting prices in nearby markets, we found that farmers' anticipated prices exhibit stronger correlation with the former. Because searching for market information (in particular price information) is costly, smallholders would have a cost-effective and more efficient price expectations if they could rely more on planting time prices than on previous harvesting prices. This is also true regarding information on wholesale prices from the central market (as a second best option). Contemporaneous central wholesale prices are superior to previous year's prices in proxying farmers' price expectations.

These findings have key research and policy implications. From a research point of view, local farm gate prices, in particular sowing season prices, serve as good proxies to model the price expectations of subsistence farmers. From a policy perspective, disseminating accurate and timely information, particularly on the current planting season cash prices of the nearby grain markets, would be critical in improving smallholders' price expectations. These findings by no means suggest that subsistence farmers are naive in their price expectations. Our results show that smallholder farmers make price expectation adjustments according to their expectations of rainfall during the growing season. The expectation of a negative rainfall shock in the coming growing crop season induces farmers to adjust their price expectations upwards. Smallholders in Ethiopia use traditional methods and their experience to form expectations of weather changes. Providing farmers with better access to weather forecasts and weather early-warning systems will be vital in improving the rainfall expectations of farmers, thereby improving their price expectations. To the extent that farmers base their production decisions on (expected) prices, information on current planting season prices can serve as a predictor of domestic food availability in the coming harvesting season. This, in turn, provides an early indicator of appropriate public food stockholding and trade policies.

Acknowledgments

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Appendix

FE-*like* price expectation results accounting for farmer education level and farm size

Dependent variable: Farmer price expectation Variables	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
Previous harvest price (local)	0.45***	(0.08)	0.40***	(0.15)
Previous harvest price (local) X education level	0.01	(0.02)		
Previous harvest price (local) X farm size			0.03	(0.07)
Sowing price (local)	0.47***	(0.07)	0.47***	(0.12)
Sowing price (local) X education level	0.01	(0.01)		
Sowing price (local) X farm size			0.02	(0.06)
Sowing rainfall	-0.18	(1.11)	0.90	(1.90)
Sowing rainfall X education level	-0.07	(0.35)		
Sowing rainfall X farm size			-0.42	(1.03)
(Expected) growing rainfall	-0.86**	(0.35)	-1.64**	(0.68)
(Expected) growing rainfall X education level	0.08	(0.08)		
(Expected) growing rainfall X farm size			0.46	(0.33)
Previous harvest price (wholesale)	0.15**	(0.06)	0.22**	(0.10)
Previous harvest price (wholesale) X education level	-0.02**	(0.01)		
Previous harvest price (wholesale) X farm size			-0.08	(0.05)
Sowing price (wholesale)	-0.11	(0.07)	-0.20	(0.13)
Sowing price (wholesale) X education level	0.02	(0.01)		
Sowing price (wholesale) X farm size			0.10	(0.07)
Intercept	99.78	(51.79)	68.30	(54.03)
Adjusted R-squared	0.90		0.90	
AIC	14 021		14 017	
BIC	14 087		14 083	
N	1 187		1 187	