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**Return to Quality in Rural Agricultural Markets**

**Evidence from Wheat Markets in Ethiopia**

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## **ABSTRACT**

In many Sub-Saharan countries, farmers cannot meet the growing urban demand for higher quality products, leading to increasing dependency on imports. While the literature has focused on production-side constraints to enhancing smallholder farmers' output quality, there is scarce evidence of market-side constraints. Using a unique sample of 60 wheat markets in Ethiopia, I examine the relationship between the price obtained by farmers and the quality supplied. Using objective and precise measures of observable (impurity content) and unobservable (flour extraction rate and moisture level) quality attributes, no evidence was found of a strong correlation between the two, suggesting that observable attributes cannot serve as proxies for unobservable ones. Transaction prices further reflect this, indicating that, markets only reward quality attributes that are observable at no cost. However, these results hide cross-market heterogeneity. Observable quality attributes are better rewarded in larger and more competitive markets, while unobservable attributes are rewarded in the presence of grain millers and/or farmer cooperatives on the market site. Both regression and machine learning approaches support these findings.

**Keywords:** Crops Quality, Markets Incentives, Agriculture, Africa

**JEL Codes:** L15, N57, O13, Q12, Q13

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# 1 INTRODUCTION

In many Sub-Saharan countries, national production of staple crops fails to meet the needs of local demand (OECD-FAO, 2016). In particular, local smallholder farmers cannot often supply higher quality products that are increasingly demanded by a growing urban population, causing further dependency on imports. A large share of the population is dependent on agriculture in SSA countries, employing most of the labor force and generating income. In this context, low-quality products may also affect farmers. Low quality reduces the price farmers can obtain, resulting in low returns for farming activities and keeping the farmers in poverty. A large body of literature has focused on production-side constraints to enhancing the quality of food production in low-income countries. Improving smallholder farmers' output quality can be hampered by various combinations of market imperfections (e.g., credit, risk, or labor), weak extension systems, and attitudinal factors (e.g., Benyishay and Mobarak 2019, Bold et al. 2017, Carter et al. 2013, Duflo et al. 2011, Kadjo et al. 2016, Karlan et al. 2014, Magnan et al. 2021, Suri 2011). Fewer studies have investigated the issue from the perspective of output markets, in other words, the extent to which producers can expect net positive returns from their investments in quality-enhancing technologies or practices (Bernard et al., 2017, Hoffmann and Moser, 2017, Hoffmann et al., 2013, Kadjo et al., 2016, Suri, 2011).

Market rewards for higher quality output depend on the extent to which quality is easily and unambiguously observable. Many attributes define an agricultural product's quality. Some are readily observable to the naked eyes, such as size, impurity, or color (hereafter *observable quality*), and can therefore be assessed at low cost. Others are only observable at a cost, such as aflatoxin for maize and groundnuts, or flour-extraction rate for wheat (hereafter *unobservable quality*). Where observable and unobservable quality attributes are strongly correlated, farmers may rely on observable quality to obtain rewards for their investment in enhancing the unobserved quality of their product. When the correlation is weak, further investment is needed to assess unobservable quality (Hoffmann et al., 2021). Using a simple model, Fafchamps et al. (2008) show that costly measures of unobservable quality attributes result in a

lower price premium for these attributes and lower investment by farmers to enhance these product characteristics.

This paper provides some of the first empirical evidence of the relationship between both observable and unobservable quality attributes and market price in rural markets. It is crucial to assess the relationship in this context, where quality certification bodies are mostly unavailable to smallholder farmers (Abate et al., 2021). The study relies on a unique set of data covering 3485 farmers in 60 rural wheat markets in Ethiopia, collected during the 2019-2020 marketing season. Each farmer gave a subjective measure of the overall quality level (i.e., high, medium, and low grade) of their wheat, alongside the expected price upon entering the market and the price obtained after the transaction was completed. Enumerators also collected a 1kg sample from each farmer and used appropriate equipment to establish independent and precise measures of observable (i.e., impurity content) and unobservable (i.e., flour-extraction rate and moisture content) quality attributes.<sup>1</sup> These measures were used to compute both an overall objective quality classification (i.e., high, medium, and low grade) and to measure each quality attribute independently. While farmers can easily improve impurity content before visiting the market, agricultural practices (e.g., technology adoption, post-harvest practices) are the main determinants of unobservable attributes.

The results show a clear positive relationship between the price obtained and overall quality classification. The results hold whether overall objective or subjective quality measures were used, suggesting that buyers recognize wheat quality in markets. In the preferred specification, a 2% to 8% price premium was observed for higher overall wheat quality. The three quality attributes were then used to measure which qualities buyers reward. No correlation was found between them, suggesting that farmers and traders cannot use observable attributes as a proxy of unobservable ones. Further, while there is a clear positive relationship between price and observable quality measures (10% purer wheat gets a 20% higher price), there is no relationship with unobservable attributes (i.e., moisture and flour-extraction rate) despite

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<sup>1</sup> Moisture content can be partially—though imprecisely—assessed by breaking wheat kernels.

significant heterogeneity across farmers and the crucial importance of these factors to millers downstream the value chain.

I extended the model proposed in [Fafchamps et al. \(2008\)](#) to account for varying market conditions that favor or inhibit quality recognition (e.g., [Bergquist and Dinerstein 2020](#), [Casaburi et al. 2013](#), [Casaburi and Reed 2019](#)). In particular, empirical evidence suggests that agricultural markets in Sub-Saharan Africa remain poorly integrated ([Moser et al., 2009](#)), face high transaction costs ([Aker, 2010](#), [Casaburi et al., 2013](#)), experience unequal levels of competition ([Bergquist and Dinerstein, 2020](#), [Macchiavello and Morjaria, 2021](#)) and limited access to infrastructure ([De Janvry and Sadoulet, 2020](#)). The extension of [Fafchamps et al. \(2008\)](#) implies that favorable market conditions such as market size, competition level, market infrastructure, and institutional arrangements lower the cost of measuring quality attributes, thereby increasing the price premium for unobservable quality.

These predictions were tested along with two market-level conditions: market-based conditions that include type of market (i.e., central district market versus secondary market) and market day competition (i.e., number of traders per farmer), and alternatives to standard market transactions with market infrastructure (i.e., presence of cooperatives and milling plants) and institutional arrangements (i.e., informal trader-farmer relationship). The results show a positive price premium on observable quality in central district markets. While more competition is associated with a higher premium for unobservable quality, the relationship disappears for the extraction rate in a two-stage least square estimate where the daily competition level is influenced by local rainfall ([Asfaw et al., 2010](#)) and the calendar of religious days ([Prunier, 2015](#)). Concerning market infrastructure, the presence of a nearby milling plant is positively related to price premiums for unobservable attributes. In contrast, the presence of a nearby cooperative is associated with higher prices for both observable and unobservable attributes. These findings derived from conventional econometric methods are largely confirmed using a machine learning approach that tested which market conditions and farmer characteristics best predict the price obtained. At market-level, this data-driven approach identified market competition, presence of cooperatives, and milling plants as key

characteristics explaining overall price differences. At the same time, quality attributes remain the strongest farmer-level predictor of price differences within a market.

Together, these results make three main contributions to the literature. First, they offer empirical evidence regarding quality recognition in developing country agricultural markets. Existing work suggests that high transaction costs prevent price premiums for unobservable attributes on local markets (Abate and Bernard, 2017, Fafchamps et al., 2008, Hoffmann et al., 2013, Magnan et al., 2021). As a result, traders are willing to pay a price premium only for perfectly observable attributes such as color, visible damage, or grain size (Fafchamps et al., 2008, Kadjo et al., 2016, Minten et al., 2013). I find additional evidence consistent with the idea that local traders reward only observable quality attributes. In line with previous work, the study also provides evidence that farmers are somewhat, but only partially, informed about the quality of their supply (Anissa et al., 2021, Kadjo et al., 2016).

Second, my study contributes to an emerging body of literature on the role of local market conditions in transactions. Limited access to information, insufficient infrastructure, and local institutional arrangements restrict farmers' ability to exploit market opportunities (Aker, 2010, Bergquist and Dinerstein, 2020, Casaburi and Reed, 2019, Deutschmann et al., 2020). Low market competition, particularly a lack of outside options for farmers to sell their produce, can reduce market price and returns for quality. Previous work on quality recognition has failed to take market conditions into consideration (Fafchamps et al., 2008, Kadjo et al., 2016, Magnan et al., 2021). The present paper adds to the literature by studying the interaction between market conditions and price premiums for unobservable and observable attributes. In particular, price premium is found to vary across competition levels for observable attributes only at no or small cost.

Third, I provide evidence of the demand-side constraints to agricultural quality upgrading. Policies have so far mainly concentrated on alleviating supply-side constraints to quality enhancement, including access to extension, credit, inputs, and risk management devices (Carter et al., 2013, Duflo et al., 2011, Harou et al., 2020, Magnan et al., 2021). However, without explicit recognition of quality in local markets, such policies have failed to ensure a radical and sustainable shift toward improving the supply of high-quality crops (Bernard et al., 2017, De Janvry and Sadoulet, 2020). Recent studies have adopted a demand-

side approach and assume that improving local traders' capacity to recognize quality will encourage farmers' supply of higher-quality products (Abate and Bernard, 2017, Bernard et al., 2017, Bold et al., 2021, Deutschmann et al., 2020, Magnan et al., 2021). In a recent randomized controlled study in the Senegalese onion value chain, Bernard et al. (2017) highlight the importance of farmers' expectations regarding market conditions on investments in quality-enhancing inputs. More precisely, they show that while supply-side constraints are unlikely to explain low-quality supply, it can be explained by uncertainty about market rewards for high quality onions. They provide evidence that farmers' awareness of changes in local market conditions results in significant and rapid responses by farmers, leading to the production of higher quality crops. The findings from this study add to the literature by further describing the role of market conditions in quality returns, distinguishing between observable and unobservable quality attributes. The remainder of the paper is organized as follows. Section 2 provides additional background information on the Ethiopian wheat market. Section 3 presents the research design and the data used. Section 4 describes the main characteristics of the markets and farmers, and provides an overview of the key variables used in the analysis. The conceptual framework is outlined in Section 5, and Section 6 presents the empirical strategy. The results are presented in Section 7, while Section 8 concludes.

## 2 ETHIOPIAN WHEAT MARKET

Wheat is one of the most important crops cultivated in Ethiopia, both as a source of food for consumers and as income for farmers. Wheat is grown mainly in the Central and Southern highlands by 5 million smallholder farmers, and it covers over 20% of the cereal production area (Minot et al., 2019, Shiferaw et al., 2014).<sup>2</sup> National processed wheat demand is growing, driven by urban growth and changes in food habits (Worku et al., 2017). Imports increasingly satisfy this demand, and now represent almost one-third of domestic consumption. Despite significant investment and policies to increase local agricultural output

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<sup>2</sup> A smallholder is a farming household with a plot smaller than two hectares.

over the last two decades, smallholders remain unable to respond to the growing national demand for higher quality wheat (Dercon et al., 2019).

High transaction costs and low quality of smallholders' output are key factors inhibiting development of the Ethiopian wheat value chain (Gebreselassie et al., 2017). Smallholder farmers have limited access to modern inputs such as fertilizer and improved seeds due to incomplete credit markets, an ineffective agricultural extension service, and climate shocks (Dercon and Christiaensen, 2011). Less than 1% of the wheat area is irrigated, making it vulnerable to drought (Seyoum Taffesse et al., 2012).<sup>3</sup> Inadequate infrastructure (e.g., few road networks, poor market information, restricted access to internet and phone networks) increases transaction costs and price volatility and reduces market integration, thereby reducing farmers' market participation (Minot et al., 2019). More recently, Ethiopia's agricultural strategy, led by the Federal Government of Ethiopia, has focused on transitioning towards smallholder farmers' inclusion and value chain development (Dercon et al., 2019, Tadesse et al., 2018). A key objective is to promote high-quality wheat production in order to achieve self-sufficiency.

Ethiopia's wheat value chain relies on a large and mostly uncoordinated network of rural middlemen (i.e., traders, wholesalers, brokers) whose influence has increased since the fall of the *Derg* Regime in 1991 (Dercon, 1995, Gabre-Madhin and Goggin, 2005, Gebreselassie et al., 2017).<sup>4</sup> Today, middlemen represent the main wheat buyers in local markets and ensure transportation from production areas (i.e., Amhara and Oromia) to urban demand centers (i.e., Addis Ababa or Dire Dawa) and to downstream actors like millers.<sup>5</sup> It is often argued that middlemen use their dominant position and informational advantage over farmers to gain market power (Osborne, 2005).

Formal grading systems and standards exist for many crops in Ethiopia, particularly wheat. Quality assessment and certification, however, are limited to large (often imported) consignments and are of limited use to smallholder farmers given their small transaction sizes (typically 200kg) and the comparatively large

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<sup>3</sup> There are two rainy seasons: (i) the short rainy season (*Belg*) occurs between March and May, while (ii) the long rainy season (*Meher*) is between June and September.

<sup>4</sup> In 1980, the *Derg* government adopted a bundle of measures, called the quota systems, which taxed both farmers and traders, restricted trading licenses, and fixed grain prices. The collapse of the *Derg* regime led to the abolition of these quota systems.

<sup>5</sup> See Figure A.1 for a detailed map of production and market flows.

fixed costs of quality assessment (Abate and Bernard, 2017, Abate et al., 2021, Anissa et al., 2021). Hence, spot market bargaining is based on weight and observable attributes (i.e., color, kernel size, foreign matter). Abate and Bernard (2017) note that traders' bargaining is not based on unobservable quality attributes (i.e., flour-extraction rate). As quality of this kind is not rewarded, farmers can only increase their income by supplying larger volumes. Traders aggregate and mix individual farmers' produce and sell the aggregate output to downstream actors (e.g., millers, pasta factories, larger traders).

### 3 RESEARCH DESIGN AND DATA SOURCES

#### 3.1 Sample selection and survey

The study was conducted in open-air markets where smallholder farmers sell their produce, mainly to traders. These markets are usually held on a predetermined day of the week throughout the wheat marketing season (Figure.A.2a). When they are held on more than one day a week, there is typically a primary market day and a secondary market day. The marketing season starts between October and January according to agro-ecological conditions, and ends with the long rainy season in June or July. Based on a market sample, Figure A.2b presents the distribution of the season's length per market, which ranges from 4 to 44 weeks, with a mean of 24 weeks.

The paper uses data collected as part of a broader project conducted in Ethiopia's main wheat-producing areas: Amhara, Oromia, Southern Nations Nationalities and Peoples' Region (SNNPR), and Tigray (Figure A.3).<sup>6</sup> In the 2018-2019 marketing season, a census of all wheat markets in the regions was conducted to collect market-level information such as the estimated number of buyers and sellers, the volume traded, season length, and market facilities. From this census, the main wheat market and a secondary market were selected within each *woreda* (i.e., district). The main wheat market corresponds to

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<sup>6</sup> The data collection is part of a randomized controlled trial interrupted in March 2020 due to the COVID-19 pandemic. More information on the project summary can be found at [Agricultural Technology Adoption Initiative](#) and [Agence Nationale de la Recherche](#).

the principal market in the *woreda* in terms of volume traded and number of participants. The secondary market was selected within 30km of the district market. It operates during the same months of the year, but usually on a different day of the week.

In each market, and for two survey rounds, enumerators collected information from 30 selected wheat farmers who came to sell wheat on the day of the survey. Two enumerators were posted at the two main market access roads and they surveyed one wheat farmer every 10 minutes from among those entering the market. The first round of the survey was conducted in December 2019 and January 2020 and the second round in March 2020, early in the wheat marketing season and at peak supply time, respectively (Figure A.4). The final sample includes 3584 farmers, 1790 for the first survey round and 1694 for the second.<sup>7</sup>

On any given day, farmers were interviewed twice: once upon entering the market and once upon leaving it (Figure B.1). In the first interview, enumerators collected personal information about the farmers (e.g., age, gender, travel time to market), their production performance (e.g., wheat plot area, volume produced), expected price, and self-assessed quality of their wheat (only in the March 2020 survey). The enumerators then purchased a 1 kg sample of wheat from each farmer to be analyzed later. They informed the farmers they would receive 25 Birr (i.e., 0.65 U.S. dollar) if they returned to answer another set of questions upon leaving the market. In the second part, the enumerators collected information on the wheat transactions the farmers had conducted that day, including price per kg and quantity sold.<sup>8</sup>

In each survey round, the enumerators collected market-level information regarding the specific market day as well as other market characteristics (Figure B.3).

### **3.2 Quality measures**

Two aggregate quality measure categories were used: (i) subjective and (ii) objective. Subjective quality is based on farmers' perception of the quality of their product and is mainly based on visual inspection and

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<sup>7</sup> Note that while the same markets were surveyed twice, different farmers were interviewed across the two survey rounds. Only 58 markets were surveyed in the second survey round due to the COVID-19 pandemic.

<sup>8</sup> All the farmers answered both interview parts, even if 1% did not sell their wheat. This high re-interview rate is unsurprising for at least two reasons. First, as the enumerators were posted at the main market entrance, the likelihood that a farmer used the same entrance twice is high. Second, farmers had an incentive to return on leaving the market as they were paid for answering the second set of questions.

experience. Subjective measures are usually considered inaccurate, while objective measures (especially observable ones) are those that drive price bargaining on the market. Objective measures rely on formal grades and standards established by national or international authorities, assessed with appropriate equipment that is generally unavailable in local markets (Abate et al., 2021). Previous studies have relied on either objective (Deutschmann et al., 2020, Hoffmann and Gatobu, 2014, Kadjo et al., 2016, Magnan et al., 2021) or subjective (Fafchamps et al., 2008) measures of observable and unobservable quality attributes.

Both approaches were combined in this paper. First, the subjective measure is the farmer's self-assessment of the quality of the wheat supply on that particular day. Farmers were asked to classify their wheat on a three-grade scale (i.e., low, medium, high). Second, three quality attributes were objectively measured using the 1 kg wheat sample purchased from the farmers:

1. **Moisture rate** assesses the water content in the wheat kernel. This affects seed quality and storage life. Weather conditions during the growing season and storage conditions after harvest affect moisture content. High moisture content decreases the grain's protein content, while low moisture content results in a hard grain with low flour yield.
2. **Test-weight** measures grain density and gives the potential flour yield. It is the most important attribute for millers. Test-weight can be affected by agricultural practices and technology adoption (e.g., varietal choice, fertilizer). Accurate measures are based on the weight of a standard volume of wheat, converted into kilograms per hectoliter. High test-weight indicates that the grain is well filled, resulting in a higher flour yield.
3. **Impurity rate** is the share of foreign matter such as stone or other cereals in the sample. Low impurity means that the grain sample is free of foreign elements. A grain sieve is used to separate foreign matter from a 100g wheat sample. The residues are then weighed to give the impurity rate.

It is costly and time-consuming for farmers to improve moisture content and test-weight, requiring investment in agricultural practices and technologies at planting and harvesting time. However, farmers can use traditional drying, sorting, and cleaning methods to reduce impurity levels before going to the market. It is important to note that moisture and extraction rates are defined as unobservable attributes as they are not readily observable to the naked eye, whereas impurity is fully observable. Each of these dimensions was graded on a three-point scale based on the government's official grading system. An aggregate grade (i.e., low, medium, high) was then computed using the lowest factor approach.<sup>9</sup> This resulted in a minimum quality process, adopted for simplicity, and usable in a real market context.

### **3.3 Additional Data Sources**

#### **3.3.1 Precipitation data**

The Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) daily rainfall estimates were used for the precipitation data set. Sparse or non-existent ground weather stations in developing countries have led to increased adoption of satellite rainfall estimates. CHIRPS is a daily precipitation data set developed by the Climate Hazards Group (Funk et al., 2015), which provides information at a 0.5 arc-degree resolution. Dinku et al. (2018) demonstrate that CHIRPS estimates are the most accurate data in Ethiopia (and East Africa), despite lower accuracy in mountainous or coastal areas.

An instrumental variable strategy was used to identify the causal effects of market day competition on market price. Two of the instruments are based on precipitation information (further details about the empirical strategy are presented in Section 6). Precipitation data was collected from CHIRPS at market level for the study period (December 2019 to March 2020). (i) Wet market days and (ii) heavy rain (i.e., higher than 10 mm) were thus identified in the seven days before the market day.

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<sup>9</sup> Grade and Standard institutions usually rely on the lowest factor approach to aggregate compliance with various standards into a single grade dimension: a product is given the quality grade corresponding to the lowest standard satisfaction in any considered dimension.

### **3.3.2 Population density data**

A source of remotely sensed data was used to estimate the potential relationship between market price and population density. Population density was assessed in the *kebele* (i.e., village) where the markets were located using buildings recorded in Facebook's Data for Good program (Facebook, 2021). A *kebele* is the smallest administrative unit in Ethiopia. Since each market is localized in a distinct *kebele*, a specific population density measure it thus provided for each market.

The main advantage of this data over other high-resolution datasets, such as Open Street Maps, is that it consistently covers the whole study region. Maps are built by training a neural network algorithm over house satellite images. The primary output provides a 30-meter spatial resolution map showing whether at least one house is found (example in Figure A.5). The map obtained is then combined with available census data and other population datasets to provide population estimates within the selected area. Tiecke et al. (2017) tested this approach to identify building and found it accurate in 18 developing countries (including ten from Africa). Table 1 presents summary statistics from this data.

## **4 DESCRIPTIVE EVIDENCE**

The following section describes the wheat markets and smallholder farmers in greater detail, as well as descriptive evidence of the quality supply, the relationship between unobservable and observable attributes, and the farmers' perception of their supply quality.

### **4.1 Open air rural wheat markets**

Table 1 presents summary statistics on market characteristics and market day conditions. The top panel displays time-invariant market characteristics such as the presence of price information board, the presence of millers or cooperatives, the length of the season, and market location at national and *woreda* level. Market-day specificities are displayed in the bottom panel, including enumerators' estimates of the number of sellers and buyers on a given day.

Market conditions are heterogeneous. As in [Bernard et al. \(2013\)](#), there is unequal distribution of cooperatives across markets: 60% of farmers have access to a market with a cooperative, and while millers are major wheat value-chain actors, only 54% of farmers sell wheat at a market with or close to a mill. Only one market has a price information board.

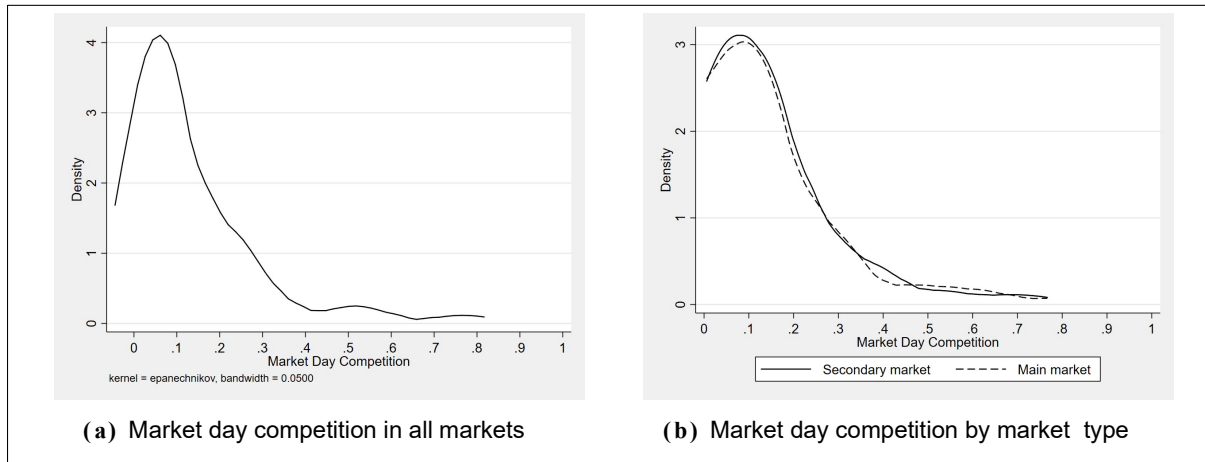
On average, 40 traders and 560 farmers from nearby localities gather on market days. The ratio of the number of traders per farmer was used as the main indicator of competition, similar to [Krishna and Sheveleva \(2017\)](#).<sup>10</sup> On average, there are 13 traders per 100 farmers on any given market day, albeit with significant heterogeneity. Figure 1a presents the distribution of competition on given market days, distinguishing between main and secondary markets. The distribution is skewed to the right with a lower number of traders per farmer. No clear difference in competition across main and secondary markets was found, despite significant differences in the number of farmers and traders across market types (Figure 2). This is confirmed by the formal tests presented in Table A.3.

**Table 1: Market characteristics**

	Mean	SD	N
<b>Top Panel: time-invariant market characteristics</b>			
Length of the season (weeks)	24.2	14.16	60
Number of supply villages to the market	11.6	14.92	60
Price information board (0/1)	.017	.13	60
Miller (0/1)	.54	.5	60
Cooperative (0/1)	.61	.48	60
Distance to Addis Ababa (kms)	352.05	200.38	60
Distance to district town (kms)	8.05	9.18	60
Kebele population	16,310	2,443	60
Kebele population density (people/km <sup>2</sup> )	1,876	2,442.75	60
<b>Bottom Panel: market-day specificities</b>			
Religious day (0/1)	.07	.26	118
Market day rainfall (0/1)	.25	.44	118
Pre-market week rainfall (0/1)	.14	.351	118
Number of traders	39.94	58.13	118
Number of farmers	560.29	611.69	118
Number of traders per farmer	.13	.15	118

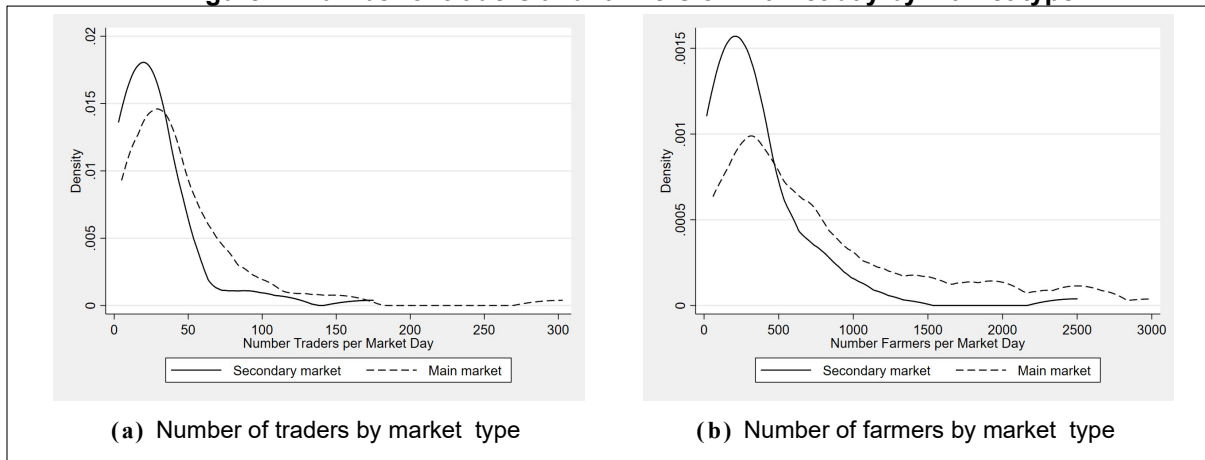
<sup>10</sup> To facilitate interpretation, the variable was multiplied by 100 to rescale.

**Figure 1: Market day competition in all markets and by market type**



Source: Author's computation based on 2019/2020 wheat markets survey.

**Figure 2: Number of traders and farmers on market day by market type**



Source: Author's computation based on 2019/2020 wheat markets survey.

## 4.2 Smallholder farmers

The sample comprises of mostly small-scale wheat producers (Table 2) with an average of 0.98 Ha of cultivated wheat and an average production of 2.7 tons. These data are similar to those observed by [Minot et al. \(2019\)](#) in their detailed analysis of the Ethiopian wheat supply chain. Yields per hectare are low compared to the most productive countries at both continental and global levels. Smallholder farmers are mainly located in isolated areas and take about one hour to reach the marketplace. Transactions are small: half of the farmers supply less than 50kg of wheat per transaction, corresponding to one standardized bag.

Lastly, as the Ethiopian wheat market is characterized by high transaction costs, no formal contracts, and a lack of formal institutions, over half the farmers are involved in relational contracts with traders. Relational contracts are necessary contractual arrangements in rural markets. They can have several purposes, such as minimizing contract breach risk when formal contract enforcement is lacking (Fafchamps, 2001) or ensuring input provisions (Ghani and Reed, 2017).

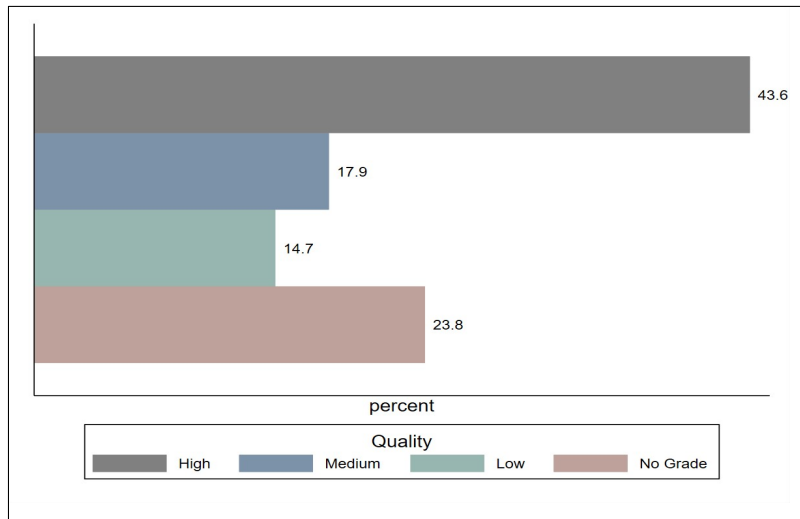
**Table 2: Farmer characteristics**

	Mean	SD	N
<b>Farmer characteristics</b>			
Age	36.37	13.58	3,484
Female (0/1)	.46	.49	3,484
Travel time (min)	58.01	46.14	3,483
<b>Agriculture variables</b>			
Wheat hectares cultivated	.98	.90	3,484
Wheat production (kgs)	2,723.26	3,431.44	3,484
Quantity sold (kgs)	83.08	129.95	3,484
Trader relationship (0/1)	.54	.49	3,484
Sold to usual trader (0/1)	.56	.49	3,444
Price expected in birr/kg	14.38	2.23	3,484
Transaction price in birr/kg	13.73	2.21	3,444
<b>Objective quality</b>			
Impurity	6.59	4.74	2,758
Moisture	12.67	2.37	2,895
Test-weight	75.33	6.29	2,764

### 4.3 Quality supply

As explained above in Section 3, enumerators collected samples from farmers on market day and tested them for test-weight, moisture, and impurity content to obtain objective quality measures. Based on the overall grade, Figure 3 shows that 43% of the wheat sample was measured as high quality, while almost 40% was of low quality at most (with low quality and no-grade grouped together). Quality distribution was consistent across the two survey periods (peak supply time and end of marketing season) (Figure A.7), suggesting an absence of time-arbitrage (Kadjo et al., 2016).

**Figure 3: Quality distribution**

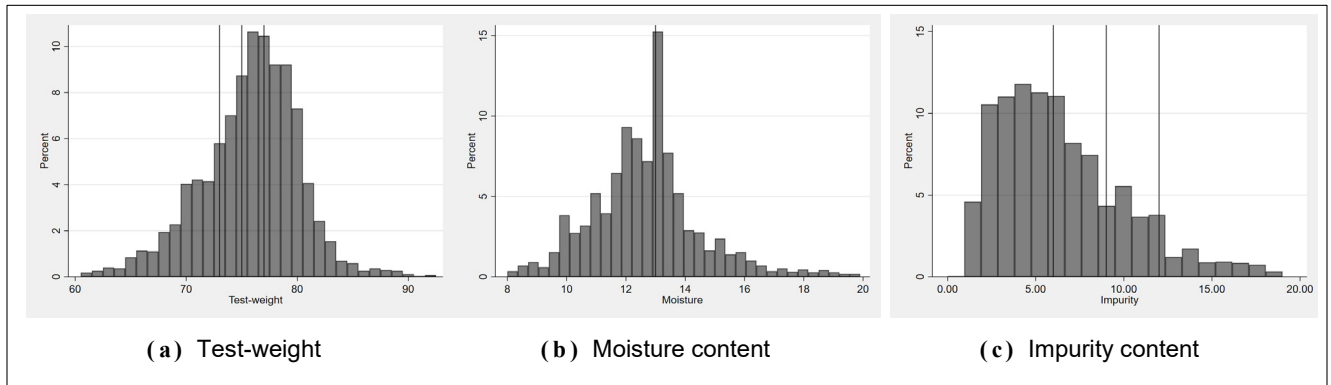


Source: Author's computation based on 2019/2020 wheat growers' survey.

Turning to each quality attribute separately, Figure 4 displays their distributions in the sample. As discussed in Section 3, test-weight and moisture are unobservable attributes, while impurity content is an observable attribute.<sup>11</sup> Accordingly, a larger distribution of unobservable attributes was observed (4a and 4b) compared to the observable attribute (4c) across the different grades. For impurity, less than 1% of the wheat was not graded (i.e., below the lowest quality standard). In comparison, the proportion of non-graded wheat reached almost 20% for test-weight and moisture. These differences may reflect the costs associated with producing higher quality for these attributes. While reducing impurity is inexpensive (e.g., cleaning and sorting), enhancing test-weight and moisture require additional investment in inputs and practices. The differences may also reflect the absence of a price premium for these unobservable dimensions, reducing farmers' incentive to upgrade quality in these areas. It can also come from farmers' unawareness about unobservable attributes.

<sup>11</sup> See Table A.1 for quality attribute thresholds.

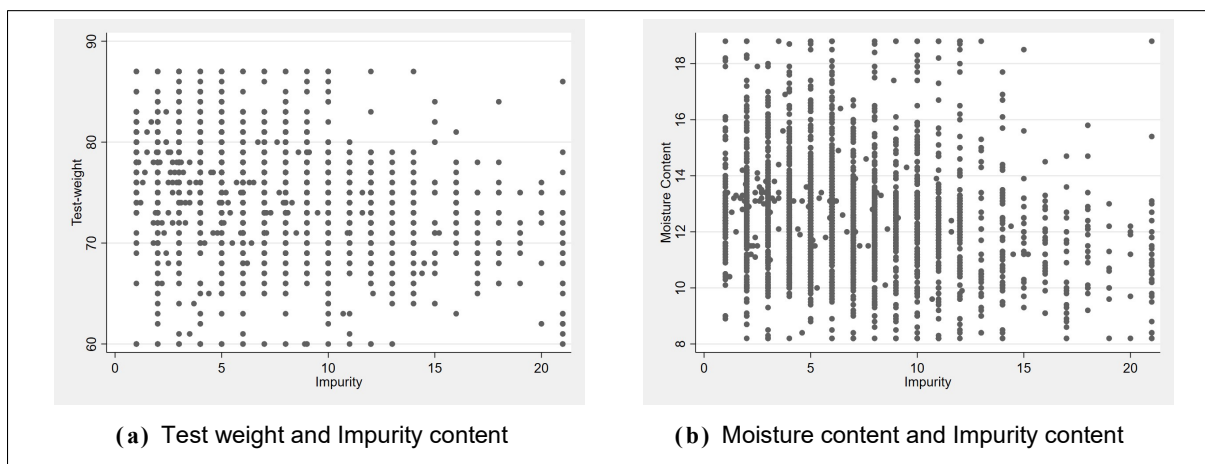
**Figure 4: Quality distribution by criteria**



Source: Author's computation based on 2019/2020 wheat growers' survey.  
 Notes: vertical lines represent the threshold for different grades. For test-weight: low grade is for values between the two left vertical lines; medium grade is for values between the two right vertical lines; high grade is for values higher than the rightmost line. For impurity content: low grade is for values between the two right lines; medium grade is for values between the two left lines; high grade is for values smaller than the leftmost line. For moisture content: wheat is considered as no grade if the result is on the right of the vertical line.

Figure 5 investigates the correlation between observable (i.e., impurity) and unobservable (i.e., test-weight, moisture) quality attributes. A high correlation would imply that farmers or traders can rely on observable attributes to infer the level of unobserved ones (Barzel, 1982). However, no strong relationship can be observed in Figure 5, such that farmers and traders cannot rely on impurity to estimate test-weight or moisture level.<sup>12</sup>

**Figure 5: Relationship between unobservable and observable characteristics**

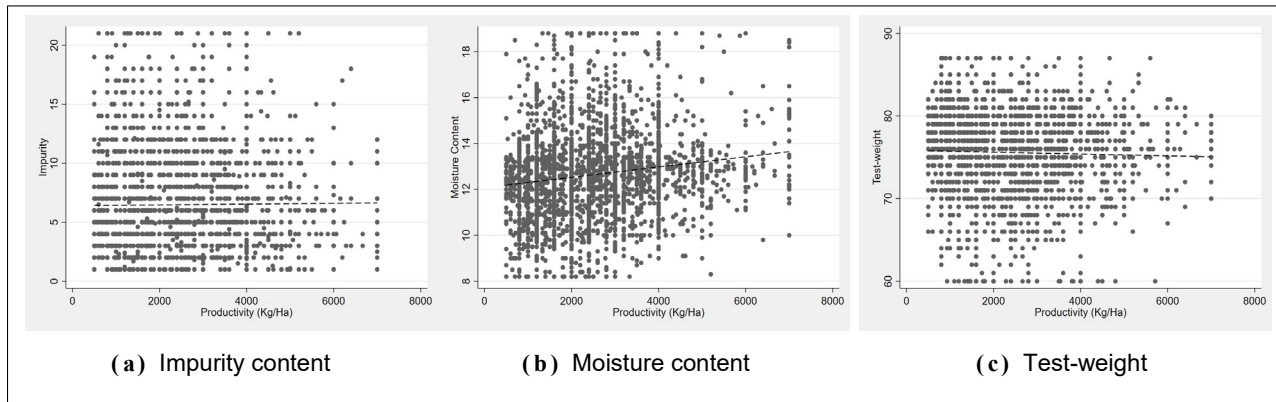


Source: Author's computation based on 2019/2020 wheat growers' survey.

<sup>12</sup> The correlation coefficients between impurity and unobservable attributes are 0.14 and 0.18 for moisture content and test-weight, respectively. The literature seems to consistently suggest that correlations below 0.2 are at most very weak (Evans, 1996) or small (Cohen, 1988; Lovakov and Agadullina, 2021).

Moreover, smallholder farmers are liable to face a trade-off between supplying high-quality wheat or increasing productivity according to expected returns. For instance, farmers are more likely to supply larger volumes rather than higher quality if traders do not pay a premium for high-quality wheat. If market prices are based on weight alone, the only way for farmers to increase their revenue is to raise productivity and thus their supply volume. This should result in a negative relationship between productivity and supply quality. However, I only found a correlation between productivity and moisture content (Figure 6b), even though the link is weak (i.e., the correlation coefficient is equal to 0.15). In other words, the more productive a farmer, the higher their wheat's moisture content. Given storage condition constraints, it may be harder for farmers to store wheat well enough to prevent moisture increase. The findings suggest that farmers tend not to specialize in either high-quality or high-volume production.

**Figure 6: Relationship between quality attributes and productivity**



Source: Author's computation based on 2019/2020 wheat growers' survey.

I then examined farmers' assessment of the quality of their produce. The subjective quality measure is compared with the objective estimates. As seen in Table 3, only 28% of farmers accurately estimated the quality of their output, while 26% underestimated it, and 46% overestimated it. Thus, in line with [Anissa et al. \(2021\)](#), farmers are somewhat, but only imperfectly, aware of the quality of their produce. Two reasons may explain this gap. First, farmers rely on an incomplete vector of mainly observable quality attributes for

their assessment. Second, farmers perceived the enumerators as government agents and so overrated their products to satisfy them.<sup>13</sup>

**Table 3: Farmers' quality prediction by subjective quality**

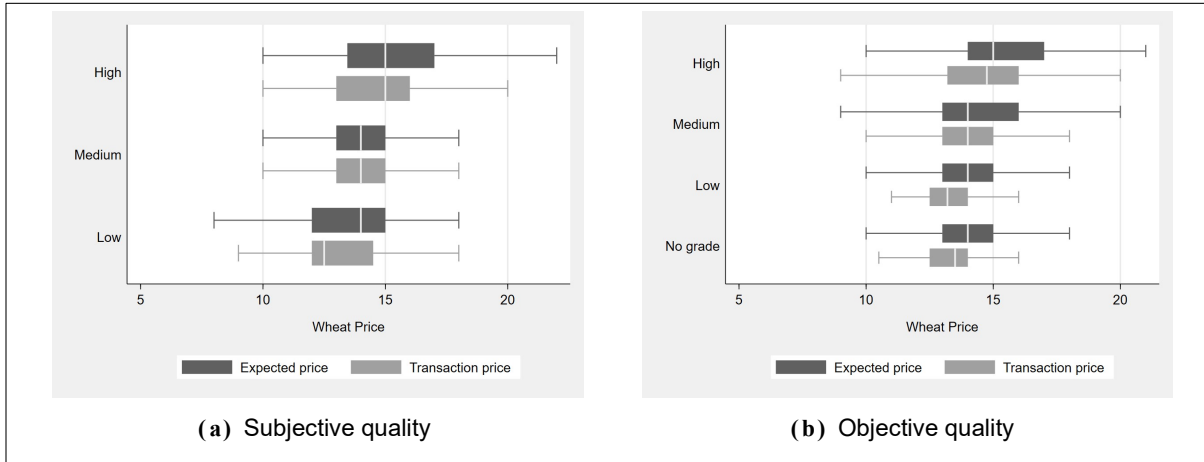
Prediction	Subjective quality			Total
	High	Medium	Low	
Accurate estimation %	48.1	16.7	42.6	28.3
Underestimation %	0.0	36.6	51.5	25.8
Overestimation %	51.9	46.7	5.9	45.9
Total %	100.0	100.0	100.0	100.0

Source: Author's computation based on 2019/2020 wheat survey.

Lastly, the farmers' expected price is compared with the effective market price they obtained by overall objective and subjective grade. As Figure 7 shows, expected prices tended to be slightly higher than market prices. Further, expected and market prices are positively correlated with both objective and subjective aggregate quality assessment, suggesting that farmers have fairly good market price knowledge. This may suggest that they can bargain to obtain higher prices based on quality expectations. It could also reflect farmers' awareness of the current market state. Finally, the figure shows greater price dispersion for objectively higher quality wheat than for lower quality. Further details of farmers' price prediction accuracy are presented in Table A.5, showing that the precision of price estimation is positively correlated with the subjective grade but not with the objective one.

<sup>13</sup> In line with a Hawthorne effect.

**Figure 7: Price and expected price (in Birr/kg) by objective and subjective quality**



Source: Author's computation based on 2019/2020 wheat growers' survey.

## 5 CONCEPTUAL FRAMEWORK

It is widely accepted that the price of a good depends on the reward for its observable attributes. When information on a given attribute is not available without cost, the market will not reward producers for the attribute in question, and the producer will have no incentive to supply it. In the context of crop markets in SSA, some attributes are unobservable to the naked eye and can only be assessed at a given cost. Building on the initial Lancaster (1966) model, Fafchamps et al. (2008) propose a conceptual framework to analyze return to quality in developing countries' agricultural markets. Wheat markets in Ethiopia are similar to their settings in that information for some attributes is not freely available.

Fafchamps et al. (2008) model the supply and price premiums in non-staple crops in India for crops with observable and unobservable attributes  $k$ . When information about an attribute is available in the market, a buyer is willing to pay a price premium  $\alpha$  to reward its presence. On the other hand, the buyer must pay an inspection cost  $c$  when information for a given attribute is not available. Buyer utility levels are noted  $U_1$  and  $U_0$  for the crop with and without the attribute, respectively. Using this model, they first show that buyers will only pay for attributes for which information is available in the market. Thus, for a perfectly observable attribute, there is a price premium equals to the utility gain from the attribute (i.e.,  $\alpha = U_1 - U_0$ ). However, the price premium shrinks in line with the increase in inspection costs, and can

even disappear for prohibitively high inspection costs, clearly illustrating that inspection costs required to reveal an attribute's value impede market recognition of weakly observable attributes. Indeed, when an attribute is unobservable, traders will not reward it and consequently farmers will not supply it.

However, only homogeneous market conditions were taken into consideration in [Fafchamps et al. \(2008\)](#)'s research. The present study extends the framework to heterogeneous market conditions. Market conditions can be defined as any market characteristic that affects transaction costs, such as competition, remoteness, presence of cooperatives, and so on. Better market conditions imply better infrastructure in the physical marketplace, such as the presence of certified scales, moisture meters, and sorting tables. Market condition  $\theta$  is continuous and normalized as in  $\theta \in ]0,1]$ . The cost to assess quality decreases as market conditions improve (i.e.,  $\theta \rightarrow 1$ ) and increases as market conditions worsen (i.e.,  $\theta \rightarrow 0$ ). Let the cost to assess quality now be denoted as  $c = c^{1-\theta}$ . This has no effect on price premium for easily observable attributes as they are freely observable. However, it does have an impact with regard to weakly observable attributes. It is easy to verify that the equilibrium price premium ( $\alpha^*$ ) decreases when market conditions are less profitable. Otherwise, inspection costs fall as market conditions improve. As the latter improve, traders have access to better infrastructure and thus more information, reducing the transaction costs for measuring quality.

In the empirical analysis, two assumptions underlying this model were tested, together with two hypotheses generated by it.

**Assumptions:**

1. For a perfectly observable attribute, a price premium equal to the buyers' utility gain results from the presence of the attribute. The price premium shrinks for weakly observable attributes due to a rise in the quality inspection costs. For a prohibitive inspection cost, there is no price premium.
2. It is less expensive to assess unobservable quality attributes under better market conditions. As a result, the price premium for a given unobservable attribute will be higher in a market with better

conditions. However, for a cost that is high enough to measure a given attribute, the associated price premium will be null.

**Hypothesis:**

1. Traders pay a price premium for purest wheat, not for moisture content and test-weight.
2. To the extent that the cost to measure moisture content is lower than test-weight, moisture content will be rewarded under market conditions that slightly reduce inspection costs. Test weight can be rewarded only under market conditions that significantly reduce inspection costs. Purity will be rewarded under all market conditions.

**6 EMPIRICAL STRATEGY**

Following the analytical framework above, I describe now the empirical strategy to estimate price returns to observable and unobservable quality attributes in rural Ethiopian wheat markets.

**6.1 Econometric approaches**

The price-quality relationship is estimated using the following equation based on ordinary least squares estimates:

$$\ln Y_{ijkt} = \beta_0 + \beta_1 Q_{ijkt} + \beta_2 X_{ijkt} + \beta_3 X'_{jkt} + \gamma_j + \mu_t + \epsilon_{ijk} \tag{1}$$

where  $Y_{ijkt}$  is the wheat price per kg obtained by farmer  $i$  in market  $j$  located in *woreda*  $k$  at time  $t$ .  $Q_{ijkt}$  represents the wheat quality of farmer  $i$  in market  $j$  in *woreda*  $k$  at time  $t$ . This variable may alternatively be the overall grade or the measured quality level for each attribute separately. Vector  $X_{ijkt}$  includes farmer-level variables (i.e., age, gender, yearly wheat production, wheat plot area, travel time to market, wheat type, quantity sold on market day), and the vector  $X'_{jkt}$  includes market-level characteristics (e.g., the overall volume traded) at time  $t$ . The terms  $\gamma_j$  and  $\mu_t$  are market and time (i.e., survey week) fixed effects,

respectively. Standard errors  $\epsilon_{ijk}$  are clustered at the *woreda* level.<sup>14</sup> The primary null hypothesis to be tested is whether  $\beta_1 = 0$ : price differs by wheat quality.

I then examine whether quality recognition varies with market conditions. Two categories of market conditions are considered: (i) market-based, and (ii) alternatives to standard market transactions. The market-based condition is defined as market characteristics directly related to spot market transactions between farmers and traders. I use two measures of market-based conditions: the market type (i.e., district or secondary market) and the level of competition on market day (i.e., number of traders per farmer). Alternatives to standard market transactions correspond to the different ways transactions are organized other than traditional spot market exchanges. These alternatives are measured using three variables: (i) whether the farmer has an informal relationship with a trader, (ii) existence of a mill near the market site, and (iii) existence of a wheat producer cooperative on the market site. Quality price premium heterogeneity is estimated by market conditions using the following equation:

$$\ln Y_{ijkt} = \beta_0 + \beta_1 Q_{ijkt} + \beta_2 C_{jkt} + \beta_3 (Q_{ijkt} \times C_{jkt}) + \beta_4 X_{ijkt} + \beta_5 X'_{jkt} + \gamma_j + \mu_t + \epsilon_{ijk} \quad (2)$$

where  $C_{jkt}$  corresponds to the market condition at period  $t$ . The primary null hypothesis to be tested is whether  $\beta_3 = 0$ : the relationship between price and quality depends on market conditions.

However, most of the market conditions are quite plausibly endogenous. For instance, the presence of cooperatives or the market type are likely to be an outcome of past agricultural policies. Otherwise, a farmer's decision to use an alternative to the standard market transaction process depends on unobserved factors and can also affect the return to quality. However, this bias cannot be resolved for market alternatives for at least two reasons. First, they can have long-term effects and spillover on farmers' marketing and agricultural performance, and on market transactions. Second, no administrative data or data on the previous marketing season was available to control for non random choices in infrastructure provision. Hence, the results of these variables are limited to a correlation relationship.

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<sup>14</sup> Following recommendations by [Abadie et al. \(2017\)](#), standard errors are clustered at *woreda* level, which corresponds to the sampling process level.

However, market day competition varies for a given market during the marketing season, and some exogenous factors may explain this variation. Indeed, market day competition is (quite plausibly) endogenous for at least two reasons. First, unobservable factors can affect both traders' and farmers' behavior and consequently their market participation. Second, the relationship between competition and price may suffer from reverse causality bias. Indeed, markets within a *woreda* are close, and this may result in spatial arbitrage by actors in their decision to participate in a given market. For instance, high-quality produce farmers can decide to sell their output in central markets to get a better price. Thus, the exogeneity assumption  $E[\epsilon_{ijk}|C_{jkt}] = 0$  may be violated.

To identify the causal effects of market competition on market price, an instrumental variable (IV) strategy was adopted, based on the occurrence of holy days on market day, pre-week and market day rainfall as market competition instruments. Religion has been embedded in Ethiopian society for centuries, and religious days remain significant and are widely celebrated (Prunier, 2015). As market sales are a source of cash for farmers, religious days may increase their participation in markets to finance these celebrations (e.g., to buy specific food items).

The recent literature has also investigated the relationship between rainfall and agricultural market performance. Rainfall has several implications on farmers' participation in markets and on volume traded due to poor road access (Salazar et al., 2019). Limited access to modern storage is another factor that makes farmers dependent on weather conditions (Hoffmann et al., 2021). Precipitation increases the risk of rot in unstored crops and affects farmers in their marketing decisions. For instance, rainfall may lead farmers to sell their wheat earlier than expected to avoid the risk of rot and future losses. Precipitation may also affect traders' participation in the market. If rainfall occurs either during or a few days before a market day, traders may expect farmers to be more likely to sell wet wheat. However, this would raise the traders' rot prevention storage costs. Searching costs may also be incurred to find a buyer quickly. In such weather conditions, expected net returns could be negative for some traders who may decide not to participate in the market.

I employ a two-stage least squares approach, where market competition is instrumented by whether the market day occurred on a holy day, on a rainy day, and whether heavy rainfall (i.e., over 10mm) fell in

the previous 7 days. Wheat price heterogeneity is then regressed on the predicted value of market competition and the interaction of quality and predicted competition as:

$$\text{First Stage: } C_{jkt} = \theta_0 + \theta_1 Z_{jkt} + \theta_2 X_{ijkt} + \theta_3 X'_{jkt} + \gamma_j + \mu_t + \phi_{ijk} \quad (3a)$$

$$\text{Second Stage: } \ln Y_{ijkt} = \beta_0 + \beta_1 Q_{ijkt} + \beta_2 \widehat{C}_{jkt} + \beta_3 (Q_{ijkt} \times \widehat{C}_{jkt}) + \beta_4 X_{ijkt} + \beta_5 X'_{jkt} + \gamma_j + \mu_t + \epsilon_{ijk} \quad (3b)$$

with  $Z_{jkt}$  indicating the vector of instruments. In the second stage, the wheat price per kg, ( $Y_{ijkt}$ ) is regressed on the predicted value of competition ( $\widehat{C}_{jkt}$ ) obtained from the first stage. The interaction term gives the price premium heterogeneity by competition level.

## 6.2 Machine learning approaches

I extend the analysis of the quality-price relationship using a predictive model based on machine learning (ML) methods.<sup>15</sup> ML methods have an advantage over econometric models in a few cases such as dealing with unconventional data or testing economic theory or prediction in low-dimensional settings (Mullainathan and Spiess, 2017), albeit with some significant pitfalls (Athey and Imbens, 2019, Mullainathan and Spiess, 2017). ML data-driven approaches do not rely on pre-specified parametric approaches resulting in functional form misspecification, but instead learn the relationship between variables directly from the data and optimally choose the parameters over a broad framework specific to the data.

I apply random forests (RF) and eXtreme Gradient Boosting (XGB) to predict wheat price in Birr per kg and to select the most accurate.<sup>16</sup> The algorithms were selected as they are more interpretable than Neural Networks, more versatile than Support Vector Machines, and repeated sampling makes them more accurate (Athey and Imbens, 2019). Standard procedures were followed to estimate the models.<sup>17</sup>

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<sup>15</sup> ML literature uses specific terminology. The sample used to estimate the parameters is the *training* sample. Instead of estimating a model, it is *trained*. Covariates or predictors are called *features*. The dependent variable is referred to as *response* in the context of a regression model.

<sup>16</sup> See Hastie et al. (2009) and Chen and He (2015) for more details on random forests and eXtreme Gradient Boosting, respectively.

<sup>17</sup> To estimate the ML model, the features were standardized to ensure that their scale did not influence the feature's importance. The data were then randomly split into training (70%) and test samples (30%) using five-fold cross-validation during training. Next, the wheat

The main challenge in ML algorithms relates to their interpretability. To overcome this issue, I present a measure of the importance of each feature, corresponding to the increase in the mean squared error of prediction when a given variable is randomly excluded from the model. A high feature importance increases in the mean squared error due to the predictor's omission. However, it does not indicate the sign of the association between the feature and the response (i.e., predicted wheat price). Hence, Shapley values (SHAP) were computed to increase interpretability of the XGB results.

SHAP values correspond to the unexplained part of the model for each observation, and the sign of predictors association with the response.<sup>18</sup> A positive (negative) SHAP value indicates an increase (decrease) in the overall average predicted response due to the inclusion of a specific feature. A null SHAP value means no deviation from the average mean prediction. In other words, it corresponds to the feature's contribution to the difference between the current and the average prediction. Thus, the higher an absolute SHAP value, the more important the corresponding feature is for the model.

## 7 RESULTS

In this section, I consider four different cases. First, I test whether the quality measures described in Section 4 are recognized in the market by a premium price. Second, I estimate the heterogeneous effect of quality attributes on price by market-based conditions. Third, I estimate whether alternatives to standard market transactions can help to enhance quality recognition. Finally, I use machine learning methods to identify the most important predictors of price.

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price for farmers in the 30% test sample was predicted and the relevant statistics computed (e.g., out-of-sample mean squared error and R-squared). Finally, a grid search was conducted over a range of parameter values during model training, selected to minimize errors.

<sup>18</sup> See [Amin et al. \(2021\)](#) for more details.

## 7.1 Quality price premium

### 7.1.1 Overall grade

First, the results of quality recognition are presented using objective and subjective quality measures. Table 4 shows the presence of a price premium for high-quality wheat using both quality measures.

Columns (1) to (4) show consistently positive and significant associations between quality and market price, although the introduction of market and time fixed effects in columns (2) and (4) significantly reduce the point estimates. In the most conservative estimates, I find a 2% price premium for objective high-grade compared to low-grade wheat (column 2) and an 8% premium for subjective high-grade wheat in column (4). I find similar results using farmers' expected price as the dependent variable in columns (5) to (8), suggesting that farmers producing lower quality output do indeed have lower price expectations than those producing high-quality wheat. Columns (7) and (8) report the expected price premium using the subjective quality measure. Accordingly, farmers with both high and medium-quality produce expect to earn a price 5% higher than lower-quality produce farmers. Overall, the results from Table 4 suggest that farmers are well aware of their wheat quality and that they rightly expect price premiums for higher quality output. These findings contrast with recent ones by [Bold et al. \(2021\)](#) in Uganda, who assess maize quality in a lab and fail to identify a quality-price premium for high-quality maize in a randomized experiment.

The results from Table 4 also suggest minor differences in price premium between high and medium quality wheat. This may relate to the compounding effect of aggregate quality grades, which could hide the individual effects of various attributes. These are examined these below.

**Table 4: Market and expected price premium by objective and subjective quality**

	Market Price				Expected Price			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Objective quality:</b>								
High	0.07*** (0.02)	0.02*** (0.00)			0.07*** (0.02)	0.01** (0.00)		
Medium	0.03* (0.02)	0.01* (0.00)			0.03** (0.01)	0.01 (0.01)		
<b>Subjective quality:</b>								
High			0.12*** (0.03)	0.08*** (0.01)			0.07** (0.03)	0.05*** (0.01)
Medium			0.08*** (0.02)	0.07*** (0.01)			0.05* (0.03)	0.05*** (0.01)
Constant	3.10*** (0.22)	2.41*** (0.09)	2.83*** (0.21)	2.55*** (0.03)	3.07*** (0.22)	2.40*** (0.08)	2.90*** (0.23)	2.57*** (0.03)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
Market FE	No	Yes	No	Yes	No	Yes	No	Yes
N	2901	2901	1676	1676	2901	2901	1676	1676
Number of clusters	30	30	30	30	30	30	30	30
F-test (High = Medium) p-value	0.01	0.20	0.02	0.01	0.03	0.81	0.09	0.11

Notes: Price and expected price are expressed in logarithmic form. Low quality is considered as the value of reference. Controls included: age of farmer *i*, gender of farmer *i*, yearly wheat production of farmer *i*, plot size of farmer *i*, travel time of farmer *i* to market *j*, type of wheat produced by farmer *i*, quantity sold by farmer *i*, and market day volume traded on market *j*. Standard errors (in parentheses) are clustered at *woreda* level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

### 7.1.2 Quality attributes

The extent to which an attribute can be observed may play an important role in its recognition in the market (Abate and Bernard, 2017, Fafchamps et al., 2008, Hoffmann and Gatobu, 2014). While it is possible to assess the quality of different crop attributes, testing requires lab equipment. Since a homogeneous volume of grain is needed for the test, the per kg cost of testing decreases with the overall volume of grain to be assessed. Thus, objective quality testing is rarely performed in local markets (Abate et al., 2021). The present study data allows the extent to which unobservable quality is perceived by farmers and rewarded by the market to be investigated.

The relationship between expected and market price, and objectively measured quality attributes is presented in Table 5. The impurity scale is reversed for convenience of interpretation, such that the variable increases with wheat purity. Of the three attributes, only purity (the only one that is directly observable) is valued by traders (column 1). The estimated coefficients are smaller but remain significant after introducing market and time-fixed effects in column (2). On average, a 1% increase in purity is associated with a 2% price premium—equivalent to 1 Birr/kg. In comparison, there is no reward for unobservable quality attributes, whether moisture content or flour extraction rate as measured by test-weight. Similar results are found using farmers' expected price as the dependent variable in columns (3) and (4), suggesting that farmers supplying purer wheat have higher price expectations than those supplying impure wheat. The results from Table 5 show that only the observable attribute is rewarded in markets and that farmers are well aware of this price premium.

These results are well aligned with those of other studies in Sub-Saharan Africa. In Benin, [Kadjo et al. \(2016\)](#) find a 3% lower price for insect-damaged maize. In Kenya, [Hoffmann et al. \(2013\)](#) measure an observable quality attribute, discoloration, and an unobservable quality attribute, aflatoxin content. They find that maize prices are strongly correlated with maize discoloration, but not with aflatoxin concentration. In Ethiopia, [Abate and Bernard \(2017\)](#) used test-weight as an indicator of wheat quality. They find that the average price Ethiopian wheat farmers receive does not depend on test-weight level. More broadly, the findings in the present study contribute new evidence to the recent literature on demand-side constraints for quality-upgrading. In line with [Fafchamps et al. \(2008\)](#), attributes measurable without cost are valued both in markets and by farmers.

**Table 5: Market and expected price premium for different quality attributes**

	Market Price		Expected Price	
	(1)	(2)	(3)	(4)
Impurity	0.04*** (0.01)	0.02*** (0.00)	0.04*** (0.01)	0.01*** (0.00)
Moisture	-0.02 (0.06)	0.01 (0.02)	-0.01 (0.07)	-0.01 (0.02)
Test-weight	0.05 (0.06)	0.01 (0.02)	0.04 (0.05)	0.01 (0.02)
Constant	3.05*** (0.30)	2.43*** (0.15)	3.04*** (0.29)	2.40*** (0.12)
Control	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
Market FE	No	Yes	No	Yes
N	2711	2711	2711	2711
Number of clusters	30	30	30	30

Notes: All variables are expressed in logarithmic form. Controls included: age of farmer *i*, gender of farmer *i*, yearly wheat production of farmer *i*, plot size of farmer *i*, travel time of farmer *i* to market *j*, type of wheat produced by farmer *i*, quantity sold by farmer *i*, and market day volume traded on market *j*. Standard errors (in parentheses) are clustered at the *woreda* level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## 7.2 Market-based transactions

Next, I examine whether price premiums vary with market-based conditions. I consider two market-based conditions in particular: the type of market (i.e., district and secondary markets) within the *woreda* and the level of competition on the given market day. The results are presented in Table 6 and show a significant and positive interaction between market type and test-weight on the wheat price obtained by farmers. Accordingly, a 1% increase in test-weight is associated with an 11% higher price, but only in district markets, not in secondary ones. In comparison, while there is a positive price premium for wheat purity, there are no apparent differences across market types. I do not find either a relationship between price and moisture content or effect of moisture interacting with market type was found.

Existing work on quality recognition in crop markets typically finds no price premium for unobservable attributes (Abate and Bernard, 2017, Fafchamps et al., 2008, Hoffmann and Gatobu, 2014, Hoffmann et al., 2013). Similarly, existing randomized controlled trials found that promoting information

about unobservable attributes has a positive impact on price premiums (Abate and Bernard, 2017, Bernard et al., 2017). However, these past studies only consider a single market type. My results show a difference in quality recognition for test-weight between district and secondary markets. This suggests greater buyer interest in test-weight in district markets. Indeed, it does not mean there is higher test-weight in district markets, but higher responsiveness of price to test-weight.

**Table 6: Price premium for different quality attributes, with heterogeneity by market type**

	(1)	(2)	(3)
<b>Quality variable:</b>	Impurity	Moisture	Test-weight
Quality	0.01** (0.01)	0.04 (0.03)	-0.01 (0.02)
District Market × Quality	0.01 (0.01)	-0.03 (0.03)	0.11* (0.05)
Constant	2.55*** (0.03)	2.45*** (0.06)	2.33*** (0.11)
Control	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Market FE	Yes	Yes	Yes
N	2725	2856	2731
Number of clusters	30	30	30

Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. The impurity scale is reversed: high value is now purest wheat. District market is equal to 1 if market j is the district market in the *woreda*. The quality term in the interaction variable corresponds to the quality attribute specified at the top of the column. Controls included: age of farmer i, gender of farmer i, yearly wheat production of farmer i, plot size of farmer i, travel time of farmer i to market j, type of wheat produced by farmer i, quantity sold by farmer i, and market day volume traded on market j. Standard errors (in parentheses) are clustered at the *woreda* level. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Next, I consider the relationship between competition level (number of traders per farmer) and quality recognition. This is important as traders' market power can lead to major constraints in investment decisions and quality upgrading (Swinnen and Vandeplass, 2015, 2010). In such cases, traders have no incentive to reward quality as farmers have limited outside options. Moreover, it may be harder to coordinate or collude with other traders. A larger number of traders may result in a broader diversity of the latter, including those with a higher valuation of higher-quality wheat. However, the existing literature in developing countries on the topic mainly refers to global and export-oriented supply chains (Reardon and

Hopkins, 2006, Swinnen and Vandeplas, 2010). Competition in local markets has also seen a recent rise in academic interest (Bergquist and Dinerstein, 2020, Dillon and Dambro, 2017). While Dillon and Dambro (2017) do not find lack of competition in agricultural markets in SSA, Bergquist and Dinerstein (2020) provide new experimental evidence on imperfect competition among intermediaries from maize markets in Kenya. Given that local markets remain the principal option for farmers to sell their output, it is helpful to measure the extent to which market competition plays a role in quality recognition. In particular, given the few outside options available to farmers, market competition helps to understand the importance of market conditions in quality recognition. For instance, Abate and Bernard (2017) find that Ethiopian wheat growers usually sell and buy food in their local *kebele* market and may therefore be captive to traders.

Table 8 shows how the relationship between price and quality differs with competition. Columns (2), (3), and (4) of Table 8 show that greater demand-side competition is positively correlated with market price premium, albeit average prices are lower in the most competitive markets.

However, as discussed in Section 6, there is concern that the validity of the exogeneity assumption between market competition and price is violated. Thus, I rely on an IV strategy to establish identification based on three instruments: occurrence of religious days, whether it rains in the pre-market week, and whether it rains on the market day. The interaction term which captures the heterogeneous effect of competition on quality price premium is also endogenous. Hence, I include interaction terms between instruments and quality attributes as additional instruments (Wooldridge, 2010). I first assess whether the instruments used are good predictors of competition. The results in Table 7 show that rainfall and occurrence of a religious day have a significant and negative effect on market day competition. The F-statistic of the first-stage regression associated with a test of the null hypothesis that all coefficients are zero is reported in Table 8. The F-statistic exceeds the Staiger and Stock (1997) rule-of-thumb value of 10 in the primary estimation in Column (4), indicating that the instruments are not weak. Apart from Impurity in Column (6), the F-statistic exceeds 10 in other estimates, indicating that the instruments are good predictors of competition. As I define market day competition as the number of traders per farmer, the negative relationship may be due to higher farmer participation or lower trader participation. The results in Table

A.4 show that religious days and rainfall have a positive and significant relationship with farmers' participation, possibly suggesting that farmers may sell more on a religious day to finance religious expenditure. The number of farmers in the market is higher when rainfall occurs pre-week and on market days, in all likelihood in a bid to sell wet wheat to prevent loss from rot. However, only rainfall during the week before market day has a significant and negative relationship on traders' participation. This supports the idea that some traders do not go on the following market day to avoid any additional costs linked to buying wet wheat (e.g., storage or screening costs).

**Table 7: Market price and market competition (first stage)**

(1)	
Endogenous variable	Competition
Religious day	-0.09** (0.04)
Pre-market week rainfall	-0.07* (0.05)
Market day rainfall	-0.11** (0.04)
F statistics	
Overidentification p-value	11.69
Time FE	0.06
Market FE	Yes
N	Yes
Number of clusters	3444
	30

Notes Competition is the hyperbolic sine transformation of the number of traders per farmer on market day. Religious day is a dummy equal to 1 if the market day occurred on a religious day in market j. Pre-market week rainfall is a dummy equal to 1 if rainfall is higher than 10mm in the previous 7 days in market j. Market day rainfall is a dummy equal to 1 if it rained during the market day in market j. Standard errors (in parentheses) are clustered at the *woreda* level. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Accounting for competition endogeneity modifies the results considerably. As reported in Table 8, I find that accounting for competition level endogeneity increases the price premium for impurity and moisture content compared to the OLS estimates, whereas the effect of test-weight becomes insignificant. In addition, the size of the interaction terms coefficient triples when using IV estimates in Columns (6) and (7) compared to OLS in Columns (2) and (3).

These results demonstrate that price is more sensitive to impurity and moisture as competition increases. Hence, the incentive to supply high-quality wheat is higher in competitive markets as traders offer higher price premiums for purer wheat. Since inspecting impurities does not entail additional cost for traders, rewarding purer wheat can be a differentiation strategy for them to secure the best wheat supply in a competitive environment and to subsequently obtain higher prices. While moisture is unobservable to the naked eye, field observation suggests that experienced traders can approximate it by chewing grain. Thus, some traders can measure moisture free of cost, even if it is an imperfect estimation. Given that competition between traders increases demand and alternative trading options for farmers, more traders may be interested in high-quality wheat to preserve their margins and market share. No such approximation is available for test-weight (flour-extraction rate), in line with the lack of reward in both higher and lower competition markets.

These results align with [Bold et al. \(2021\)](#), who find that the entry of buyers rewarding high quality increases the equilibrium price. In contrast, [Bergquist and Dinerstein \(2020\)](#) find that new entrants will not modify the market environment where traders have significant market power as they will join collusive agreements with the incumbents.

More broadly, the findings show that market conditions are key determinants of reward for quality. However, they also highlight the limits of market forces in rewarding unobservable crop attributes. Thus, alternatives to traditional market mechanisms can emerge as a second-best solution. These are discussed below.

**Table 8: Price premium for different quality attributes, with heterogeneity by market competition**

	OLS				2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Quality variable:</b>	None	Impurity	Moisture	Test-weight	None	Impurity	Moisture	Test-weight
Competition	-0.15 (0.09)	-0.07 (0.07)	-0.96** (0.38)	-1.48*** (0.33)	-0.14 (0.14)	0.47 (0.25)	-2.86** (1.42)	2.10 (4.12)
Quality		0.01 (0.00)	-0.01 (0.01)	-0.02 (0.02)		-0.05 (0.01)	-0.08 (0.05)	0.06 (0.09)
Competition × Quality		0.08*** (0.02)	0.31** (0.13)	0.30*** (0.08)		0.24** (0.10)	1.00* (0.55)	-0.58 (0.97)
Constant	2.58*** (0.02)	2.58*** (0.08)	2.57*** (0.10)	2.60*** (0.13)	2.62*** (0.03)	2.61*** (0.12)	2.70*** (0.20)	2.54*** (0.27)
Control	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3444	2725	2856	2731	3444	2725	2856	2731
Number of clusters	30	30	30	30	30	30	30	30
F statistics (First stage)								
Competition					11.69	6.35	14.13	10.09
Interaction term						6.86	13.57	10.00
Overidentification p-value					0.06	0.54	0.24	0.39

Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. The impurity scale is reversed: high value is now purest wheat. Competition is the hyperbolic sine transformation of the number of traders per farmer on market day. The quality term in the interaction variable corresponds to the quality attribute specified at the top of the column. Competition is instrumented by the occurrence of a religious day, pre-week market day and market day rainfall. In addition, quality interacts with the previous instruments. Controls included: age of farmer  $i$ , gender of farmer  $i$ , yearly wheat production of farmer  $i$ , plot size of farmer  $i$ , travel time of farmer  $i$  to market  $j$ , type of wheat produced by farmer  $i$ , quantity sold by farmer  $i$ , and market day volume traded on market  $j$ . Standard errors (in parentheses) are clustered at the *woreda* level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

### 7.3 Alternatives to standard market transactions

As a decentralized allocation mechanism, the market failed to recognize unobservable attributes with a price premium. [Fafchamps \(2003\)](#) states that formal institutions in SSA are inefficient due to small transaction size. As a result, market actors may use alternative mechanisms to ensure quality provision. These mechanisms can be formal, such as providing agricultural inputs through cooperatives ([Bernard et al., 2013](#), [Deutschmann et al., 2020](#)), certification services ([Bernard et al., 2017](#)), vertical integration ([Deutschmann et al., 2020](#)), or informal arrangements, such as farmer-trader relationships based on trust and repeated interactions ([Casaburi and Reed, 2019](#), [Fafchamps and Minten, 1999](#)).

I examine this issue using three variables: relationship between trader and farmer, existence of a mill near the market site, and existence of a wheat producer cooperative in the market. Each variable captures a slightly different aspect of alternatives to market. First, the farmer-trader relationship emerges as a credible alternative to minimize contract breach risk (Fafchamps, 2001). Without protection against opportunistic behavior, constructing personal trust through repeated interactions is often a reliable substitute to market allocations. While Fafchamps and Minten (1999) argue and find that quality provision is not central in a relationship, I look further by considering whether observable or unobservable attributes are valued differently. Second, value chains, like the wheat value chain in Ethiopia, can be long and involve a large number of intermediaries (Osborne, 2005). The presence of intermediaries increases final costs as each agent expects to make a profit. However, intermediaries are not the final buyers of the goods, and their quality demands only depend on those of downstream value chain actors. For example, millers are the main end buyers of wheat before its transformation into flour. Their demand is largely driven by quality, as impurity, moisture, and flour-extraction rate (test-weight) significantly affect the volume and quality of flour. Thus, the presence of a mill near local markets is expected to reduce the length of the value-chain and to result in a higher price for higher quality wheat.

Finally, I investigate the relationship between return to quality and the presence of cooperatives near the market site. From field observations, cooperatives are often interested in quality wheat that they aggregate under the cooperative's brand name. A number of them assess the quality of farmer's wheat individually before aggregating. From a farmer's perspective, however, selling to a cooperative has drawbacks in that payment is often made with a month's delay.

**Table 9: Price premium for different quality attributes, with heterogeneity by alternatives to standard market transactions**

Quality variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Impurity	Moisture	Test -weight	Impurity	Moisture	Test-weight	Impurity	Moisture	Test-weight
Quality	0.02*** (0.01)	0.05** (0.02)	-0.01 (0.03)	0.01*** (0.01)	0.05* (0.03)	-0.02 (0.02)	0.01 (0.01)	-0.03 (0.02)	-0.01 (0.03)
Relationship	0.01 (0.01)	0.11* (0.06)	-0.19 (0.21)						
Relationship × Quality	-0.01 (0.01)	-0.04* (0.02)	0.05 (0.05)						
Millers × Quality				0.01 (0.01)	-0.04 (0.04)	0.10** (0.04)			
Cooperatives × Quality							0.02** (0.01)	0.08** (0.03)	0.07* (0.04)
Constant	2.55*** (0.03)	2.38*** (0.06)	2.51*** (0.14)	2.55*** (0.03)	2.44*** (0.05)	2.37*** (0.09)	2.46*** (0.09)	2.35*** (0.09)	2.24*** (0.13)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2725	2856	2731	2725	2856	2731	2725	2856	2731
Number of clusters	30	30	30	30	30	30	30	30	30

Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. The impurity scale is reversed: high value is now purest wheat. Relationship is a dummy equal to 1 if farmer *i* is engaged in a long-term relationship with a trader. Millers is a dummy equal to 1 if millers are present on market *j*. Cooperatives is a dummy equal to 1 if cooperative are present on market *j*. The quality term in the interaction variable corresponds to the quality attribute specified at the top of the column. Controls included: age of farmer *i*, gender of farmer *i*, yearly wheat production of farmer *i*, plot size of farmer *i*, travel time of farmer *i* to market *j*, type of wheat produced by farmer *i*, quantity sold by farmer *i* and market day volume traded on market *j*. Standard errors (in parentheses) are clustered at the *woreda* level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Table 9 shows the heterogeneous price premium for each quality attribute by alternatives to standard market transactions. The effect of the farmer-trader relationship is first investigated, measured by the survey question, "Did you sell your wheat to your usual trader?". In theory, such informal contract farming can provide a commitment mechanism to resolve the asymmetric information issue. However, I do not find these effects. If anything, in column (2), I find that if markets reward moisture content at a low rate, the premium is null for farmers with a long-term relationship with their buyer. This finding matches that of earlier work by [Fafchamps et al. \(2008\)](#) in India, who find that the farmer-trader relationship is not used to ensure quality provisions or to facilitate quality inspection.

The second aspect of alternatives to traditional marketing is the presence of nearby millers. The findings are presented in Columns (4) to (6). As before, the market reward purity and moisture content

positively, although no additional rewards are paid upon the presence of a nearby miller. In contrast, the results in Column (6) point to a positive reward for unobservable quality (test-weight) with the presence of a nearby mill. In these markets, a 1% increase in test-weight score leads to a 10% price premium. In Ethiopia, millers pay significant attention to flour-extraction rate. Two bundles of wheat, identical in terms of observable attributes (e.g., impurity), may exhibit significant differences in flour-extraction rate, consequently affecting millers' profit (Abate and Bernard, 2017). The presence of an on-site mill may affect rewards to such attributes through both informational effects and reductions in the length of the value chain that otherwise dilute the incentive to procure higher quality wheat.

Lastly, the results in columns (7) to (9) of Table 9 indicate a positive effect of the presence of at least one cooperative on price rewards for all the quality attributes, whether observable or unobservable. On average, when there is a cooperative, a 1% increase in quality is associated with a 2% price premium for impurity, 8% for moisture, and 7% for test-weight. Cooperatives play a substantial role in rural markets by providing fertilizers and seeds on credit (Bernard et al., 2008, Deutschmann et al., 2020). Hence, farmers with access to cooperatives in the market may benefit from such agricultural technology and produce higher quality wheat. Indeed, 89% and 60% of Ethiopian farmers with access to cooperatives purchase fertilizers and seeds, respectively (Abate and Bernard, 2017). In Ethiopia, cooperatives usually provide quality assessments when they collect output. Once aggregated, cooperatives may either resell bulked wheat to millers or produce flour themselves. These results may inform the role that cooperatives can play in upgrading quality in local markets.

## **7.4 Geographic conditions and marketing time**

### ***7.4.1 Market location characteristics***

Several studies in SSA show that the geographic location of rural markets affects equilibrium prices (Aker, 2010, Minot et al., 2019, Vandercasteelen et al., 2018). Here, the question is examined using geographic and demographic variables related to market environment. Each variable captures a slightly different

dimension. The first is based on the market's physical distance from Addis Ababa, the main demand center. The second captures whether the market is located in one of Ethiopia's main wheat surplus areas. I use the classification established by [Minot et al. \(2019\)](#) to identify surplus and deficit production zones. The last variable captures the potential link between market price and population density ([Bernard et al., 2008](#)). In the most densely populated *kebele*, markets might be better integrated into the regional or national wheat market. These areas also derive substantial benefits from their positions in terms of economies of scale, which can reduce transaction costs. Areas with higher population density are also likely to be more urbanized and thus be subject to greater demand for quality ([Vandercasteelen et al., 2018](#)).

The results are presented in Table 10. They point to an association between a market's geographical characteristics and a price premium for unobservable quality. In column (3), I find a positive interaction between distance to Addis Ababa and reward for unobservable quality. With distance to Addis Ababa possibly correlated with differences in soil quality across market locations (and therefore unobservable quality), caution should be taken in interpreting the result as market-driven. However, as only the interaction term is significant (and not test-weight alone), it confirms that the result is market-driven rather than due to differences in soil quality. According to Ethiopia's main surplus areas, the markets' classification highlights a positive return on unobservable quality in column (6). Finally, column (9) exhibits a positive interaction between population density and return on unobservable quality.

**Table 10: Price premium for different quality attributes, with heterogeneity by locating markers**

Quality variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Impurity	Moisture	Test-weight	Impurity	Moisture	Test-weight	Impurity	Moisture	Test-weight
Quality	0.01 (0.01)	0.01 (0.03)	-0.01 (0.02)	0.01 (0.01)	0.05*** (0.02)	-0.03*** (0.01)	0.03 (0.02)	0.05 (0.07)	-0.18 (0.11)
Addis Ababa × Quality	0.01** (0.01)	0.03 (0.03)	0.11* (0.06)						
Surplus Area × Quality				0.01 (0.01)	-0.03 (0.02)	0.12*** (0.03)			
Population Density × Quality							-0.01 (0.01)	-0.01 (0.01)	0.04* (0.02)
Constant	2.45*** (0.09)	2.37*** (0.10)	2.23*** (0.15)	2.45*** (0.09)	2.36*** (0.11)	2.13*** (0.14)	2.45*** (0.10)	2.37*** (0.14)	2.21***
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2725	2856	2731	2725	2856	2731	2725	2856	2731
Number of clusters	30	30	30	30	30	30	30	30	30

Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. The impurity scale is reversed: high value is now purest wheat. Addis Ababa is a dummy equal to 1 if the market *j* is among the furthest from Addis Ababa. Surplus Area is a dummy equal to 1 if the market *j* is located in a wheat producing surplus zone. The quality term in the interaction variable corresponds to the quality attribute specified at the top of the column. Controls included: age of farmer *i*, gender of farmer *i*, yearly wheat production of farmer *i*, plot size of farmer *i*, travel time of farmer *i* to market *j*, type of wheat produced by farmer *i*, quantity sold by farmer *i*, and market day volume traded on market *j*. Standard errors (in parentheses) are clustered at the *woreda* level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## 7.4.2 Marketing time

As agriculture is mostly rainfed in SSA, farmers face risks that affect their marketing behavior during the agricultural season. Many smallholder farmers must deal with liquidity issues at harvest time to pay back agricultural loans or satisfy essential needs such as food or school fees (Dillon, 2020, Stephens and Barrett, 2011). Moreover, without access to affordable and efficient storage technology, stored outputs may suffer severe damages from fungi, rodents, mold, and insects. For these reasons, price premium on various quality attributes may differ across the dates of the survey rounds from which the data were obtained. The results are presented in Table A.6. Overall, I find only limited evidence that the transaction date is associated with differential rewards to quality. The results in column (1) suggest that traders pay a price premium for the purest wheat supplied. However, purity is not rewarded later in the commercialization season. This closely aligns with earlier work by Kadjo et al. (2016) on the rural maize sector in Benin.

## 7.5 Robustness check

I conduct some robustness checks to ensure that the choice of control variables did not bias the result. To select control variables, I rely on the post-double selection (PDS) LASSO procedure presented in [Belloni et al. \(2013\)](#). The main advantage of PDS is that it picks control variables consistently and avoids standard errors estimation issues.

Table A.7 shows the association between quality and price, independent of market conditions as above in Table 5. As demonstrated in Table 5, a price premium is only paid for impurity. Table A.9 shows the association between price and quality by market type. The results are similar to those in Table 6. Table A.10 presents the results for the association between price and quality with heterogeneity by alternatives to market mechanisms. The results are identical to those observed in Table 5.

## 7.6 Identifying the most important price determinants, a machine learning approach

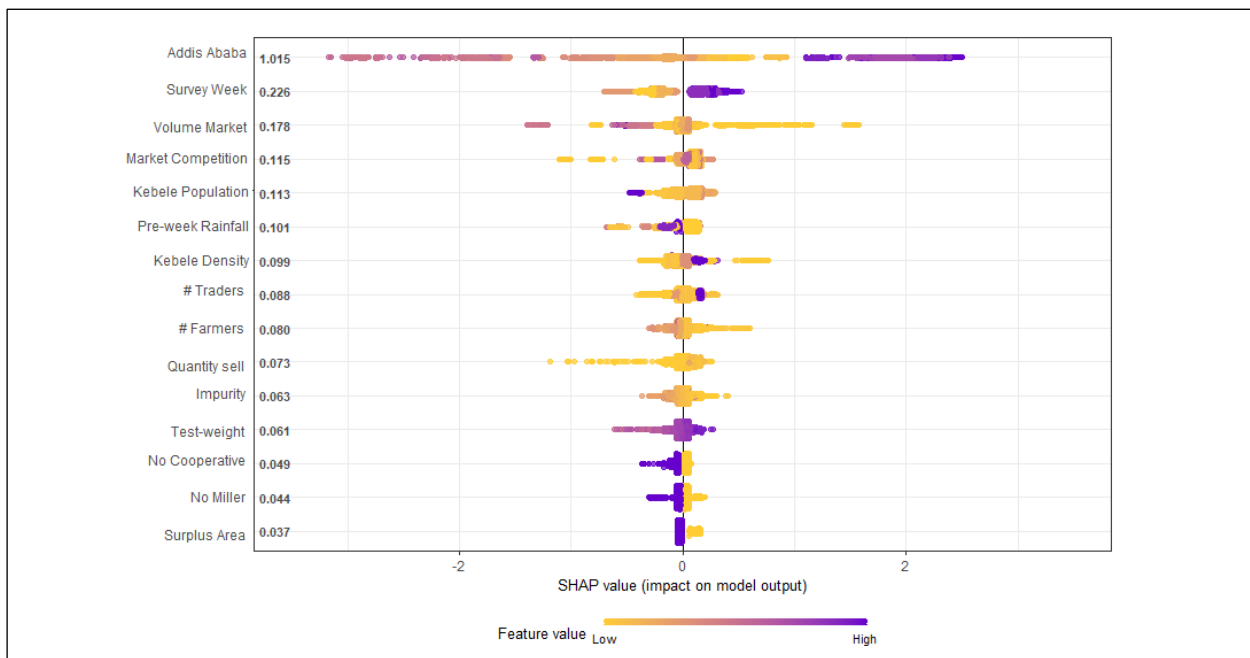
Previous work has suggested various farmer-level solutions to increase local agricultural prices ([Bergquist and Dinerstein, 2020](#), [Casaburi and Reed, 2019](#), [Karlan et al., 2014](#)). Often, this literature assumes that the main barriers to increasing price might be overcome at individual level. However, such interventions may have a limited impact if market conditions are the main price determinants. For instance, lack of infrastructure, limited information, and poor value-chain integration may prevent farmers from obtaining higher prices, and farmer-level intervention will do little to overcome them. Here, I examine whether wheat price is more likely to be determined by market or by farmer characteristics.

Table A.8 presents the out-of-sample root mean squared error (RMSE) and square of the Pearson correlation coefficient for wheat price. There is little differences in performance between random forest (RF) and eXtreme Gradient Boosting (XGB). However, the XGB model appears more accurate as the confidence interval is smaller than for RF. All the features listed in Tables 1 and 2 were used.

The aim is to determine which features are the most predictive and the direction of the association with the response. Figure 8 plots the Shapley values of the fifteen most predictive features using XGB. The

SHAP values and the features are placed on the horizontal and vertical axis, respectively. Each dot represents a farmer. The average contribution of the corresponding variable in price prediction is on the vertical axis. A positive (negative) SHAP value represents an increase (decrease) in the predicted price across all possible combinations of the predictors. For instance, the “market volume” feature decreases the predicted values (the SHAP value is negative) for most observations when included in the model. Lighter colors imply smaller values of the feature: lower values of volume traded on the market are observed where SHAP is positive. However, it is not easy to fully understand the association between the feature and the predicted price from Figure 8 alone.

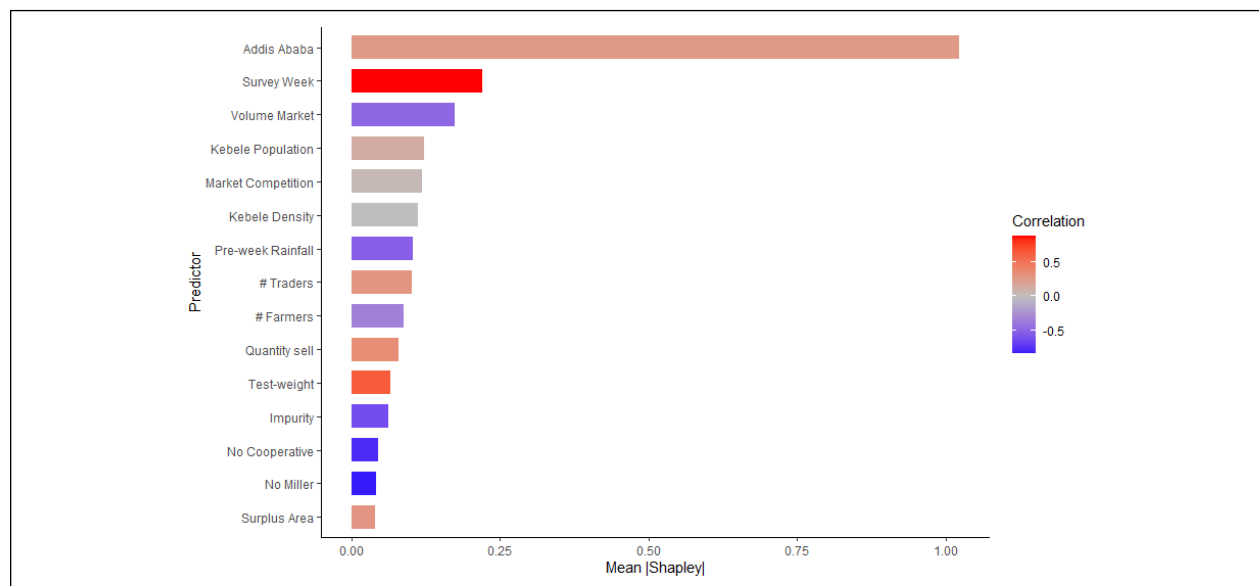
**Figure 8: Shapley values of the most predictive features of wheat price: eXtreme gradient boosting model**



Source: Author's computation based on 2019/2020 wheat survey.

Notes: Figure 8 shows the Shapley (SHAP) values of the fifteen most predictive features using eXtreme Gradient Boosting. A positive (negative) SHAP value represents an increase (decrease) in the predicted variable (i.e., wheat price per kg) across all possible combinations of the features. The mean of SHAP values indicates the variable's average contribution in prediction on the vertical axis. Darker color corresponds to higher values of the predictor.

**Figure 9: Correlation between predictive features and predicted wheat price: eXtreme gradient boosting model**



Source: Author's computation based on 2019/2020 wheat survey.

Notes: Figure 9 shows the correlation between the fifteen most predictive features and SHAP values. It provides the direction of the association (red for positive and blue for negative), and the predictor's marginal contribution in prediction based on the mean SHAP values.

Figure 9 displays an astute way to visualize the association between features and predicted prices. Average SHAP values are plotted, then colored by the correlations between the feature and its SHAP values. Distance to Addis Ababa, the survey week, and the number of traders on the market day have high positive associations with wheat price, whereas the volume traded on market day, the number of farmers, and the absence of a cooperative or a miller have a negative relationship. Moreover, the quantity sold by farmers and the test-weight values are positively correlated with price, while impurity is negatively related. Most of the best wheat price predictors are market condition characteristics rather than farmer characteristics (i.e., quantity sold, impurity, and test-weight). Otherwise, quality attributes (i.e., impurity and test-weight) are among the most important price predictors. These results support previous ones, underscoring the importance of market conditions in the analyses of price premiums for quality and farmers' incentive to invest in improving the quality of their output. Measuring and quantifying the potential effect of market conditions variation on quality price premium could be a fruitful avenue for future work.

## 8 SUMMARY AND CONCLUDING REMARKS

Food crop quality is one of the main concerns that SSA countries must address to improve returns for smallhold farming and pull farmers out of poverty. A large number of empirical studies have considered supply-side approaches to alleviate farmers' constraints in quality-upgrading, such as liquidity, risk, information, and technology access (De Janvry and Sadoulet, 2020). Following recent empirical papers focusing on demand-side constraints (Abate and Bernard, 2017, Bernard et al., 2017, Bold et al., 2021), the present study presents evidence that imperfect market recognition of quality must be addressed to enhance quality supply. Using original survey data collected in 60 Ethiopian wheat markets, I examined the extent to which quality is rewarded in the Ethiopian wheat market. I found that farmers imperfectly interpret the quality they supply, and are imperfectly rewarded for their high-quality wheat. While a significant price premium is paid to farmers for purer wheat (i.e., observable attribute), I found that low moisture content and test-weight (i.e., unobservable attributes) are not rewarded. This finding is consistent with the conceptual framework developed in Fafchamps et al. (2008) and it supports the idea that quality factors for unobservable attributes are not a current concern for traders.

Previous studies have implicitly assumed that farmers sell their output on homogeneous markets. However, market conditions are highly variable and location-specific, thereby impacting transaction costs, which may also affect quality recognition. I present evidence of quality price premium variations across market conditions and identify various market features associated with the existence of a price premium to observable and/or non-observable quality attributes. Among other things, price premiums for observable quality attributes increase with the level of market competition. In contrast, the presence of millers and/or cooperatives near market sites affects returns on non-observable quality attributes.

These findings are not based on a purposefully designed trial, and several of the highlighted relationships must be interpreted as exploratory. However, the results suggest that current policies proposed to alleviate farmers' constraints (e.g., technology adoption subsidies, financial services, and extension services development) do little to promote quality-upgrading as long as quality is not fully rewarded in the

market. Given the positive correlation between market competition and quality recognition, policymakers might be interested in promoting competition to enhance price premiums for quality, which may in turn increase farmers' returns from quality-upgrading.

However, implementing these policies in a weakly institutionalized and imperfect market context may worsen market functionality and have significant distributional effects. Market conditions are locally specific and organized around well-established rules and actors. Radical shifts in such settings may negatively affect both farmers and traders ([Macchiavello and Morjaria, 2021](#), [Anissa et al., 2022](#)). Hence, policy intervention must be evaluated on a case-by-case basis to address market issues experienced by local actors. For instance, some policies have promoted alternative marketing channels such as vertical coordination and cooperatives to enhance quality in local markets. However, they represent only a small share of local marketing channels. Other studies propose encouraging quality-upgrading through the promotion of third-party certification available to small-scale farmers to reveal unobservable attributes at low cost ([Abate et al., 2021](#)). On the farmer's side, recent evidence points to significant demand for such services ([Anissa et al., 2021](#)). The extent to which traders are willing to use such services, however, remains largely unknown.

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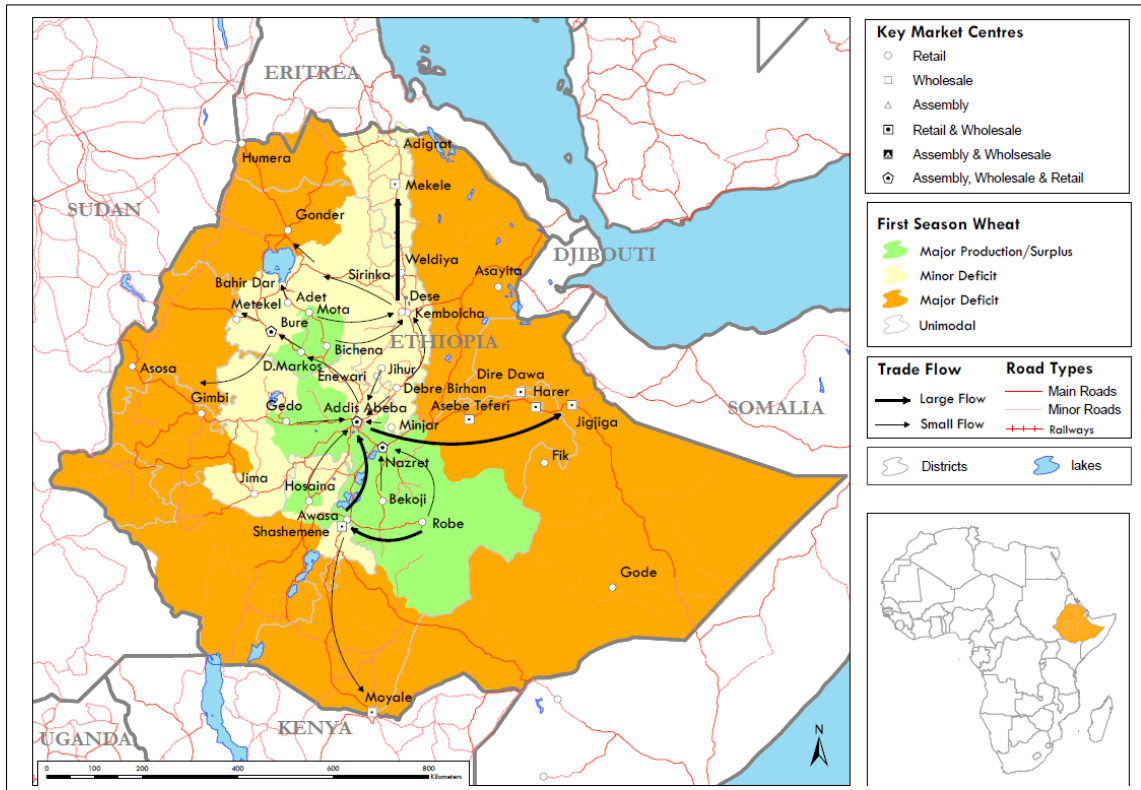
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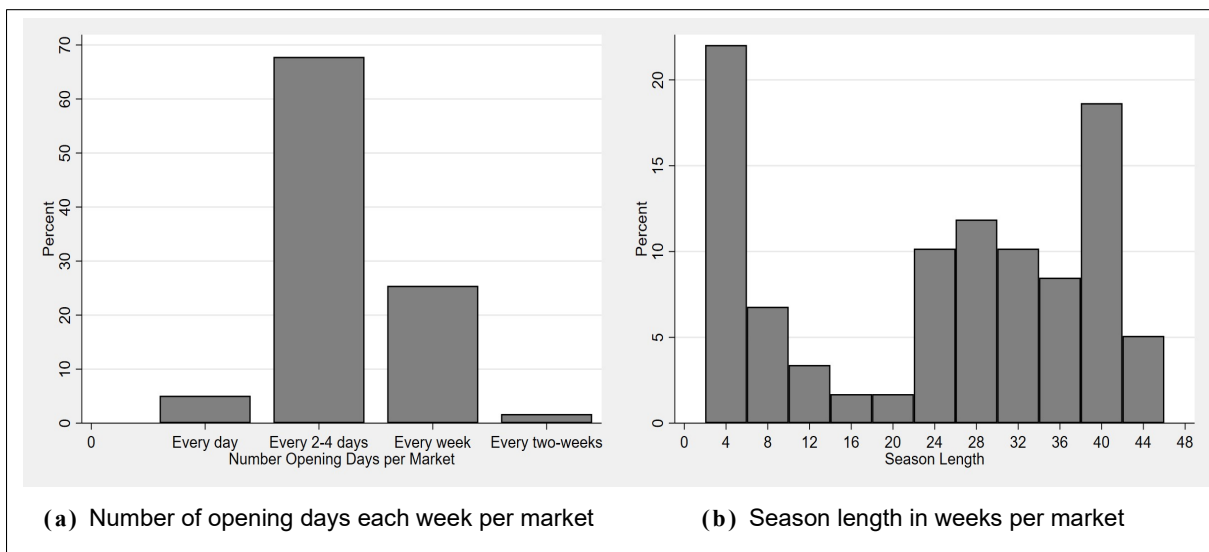
## A. APPENDIX

**Figure A.1: Ethiopian wheat production and market flow in 2010**



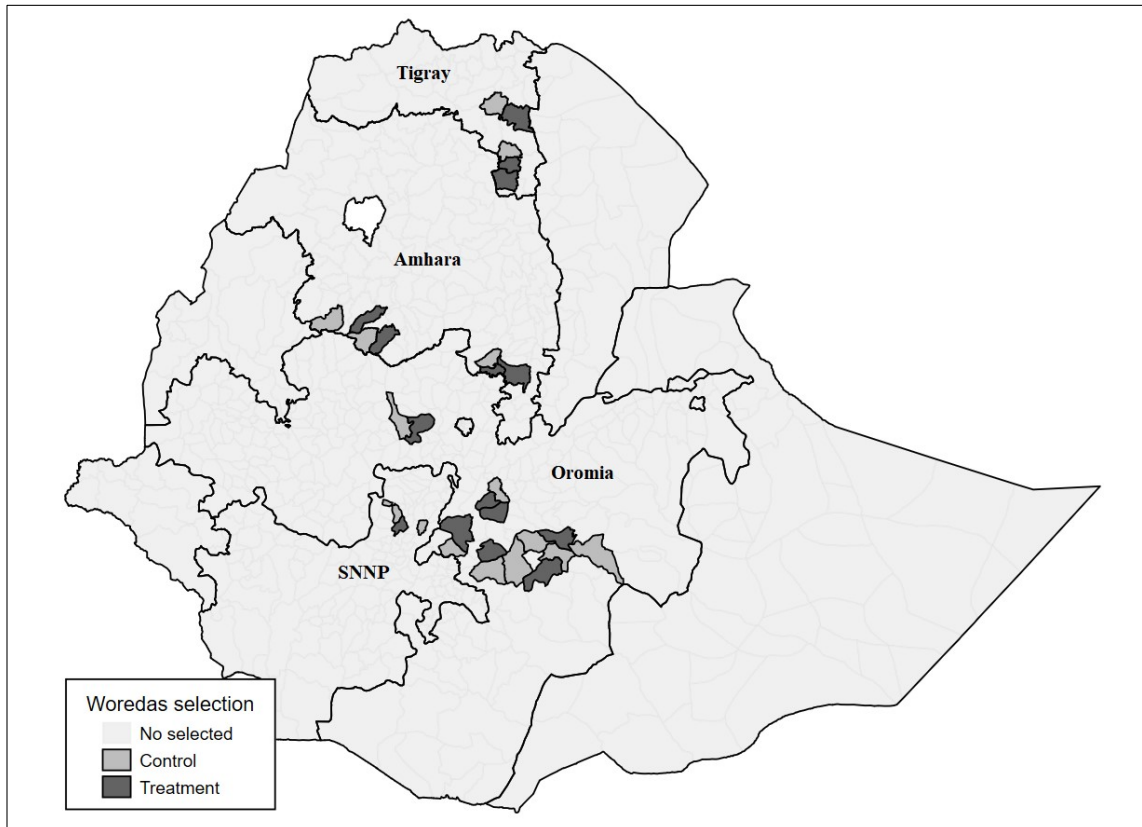
Source: FEWSNET (in FAO, 2014).

**Figure A.2: Number of opening days and season length per market**



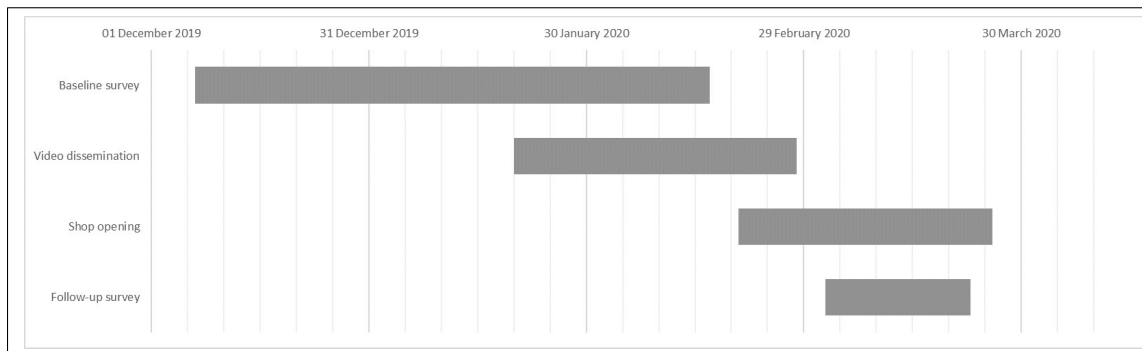
Source: Author's computation based on 2019/2020 wheat markets survey.

**Figure A.3: Study zone and initial RCT allocation**



Source: Author

**Figure A.4: Timeline**



Source: Author

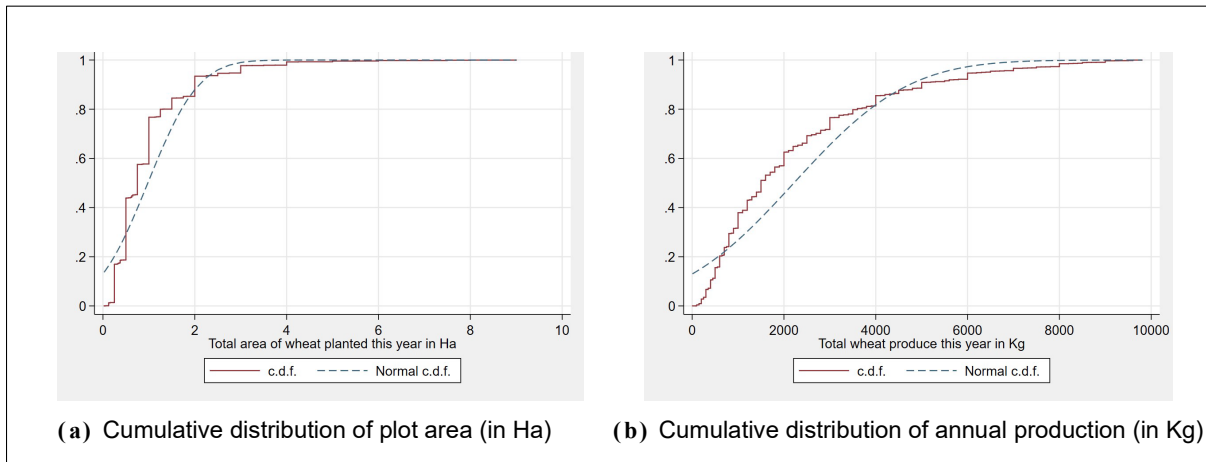
**Figure A.5: Example of Facebook population map**



Source: Google maps

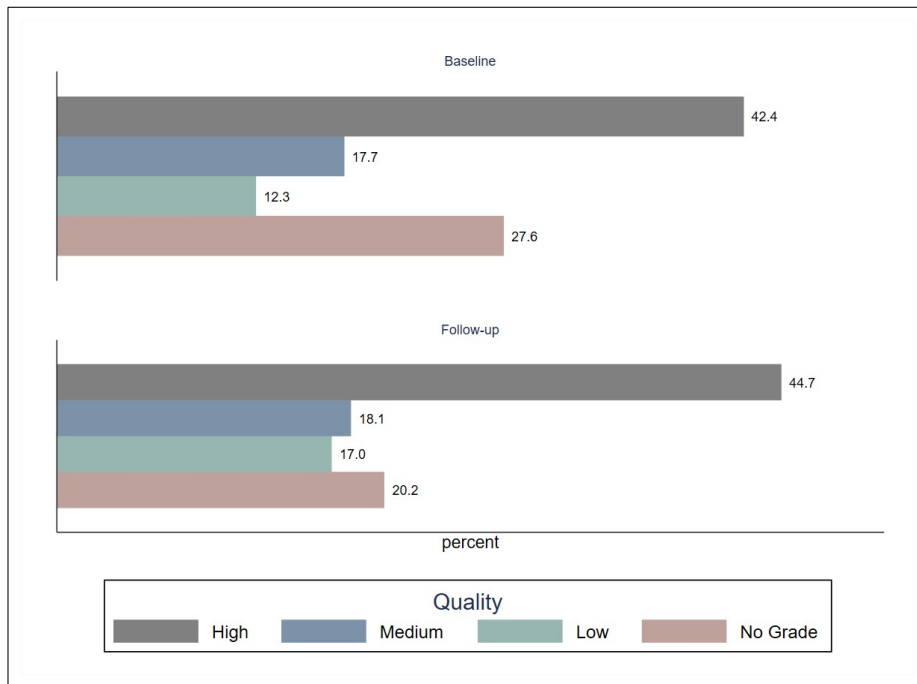
Note: Red squares indicate building detected.

**Figure A.6: Cumulative distribution of plot area and annual production**



Source: Author's computation based on 2019/2020 wheat markets survey.

**Figure A.7: Quality distribution by survey round**



Source: Author's computation based on 2019/2020 wheat growers' survey.

**Table A.1: Quality inspection format**

Grade	High	Medium	Low
Impurity content	[0;8]	]8;9]	]9;12]
Moisture content			[13;100]
Test-weight	[100;77]	]77;75]	]75;73]

Notes: Results are expressed in percentage of the wheat sample analyzed. For moisture content, we use a two-grade scale (i.e., low and high). For instance, a wheat sample with an impurity content of 6% is considered as high-quality in this dimension.

**Table A.2: Balance tests: Market participation by survey round**

	(1) Secondary Market	(2) Central Market	(3) Diff.: p-value
Competition	0.10 (0.10)	0.17 (0.18)	0.00
Number of farmers	681.98 (722.68)	447.74 (433.66)	0.00
Number of traders	30.55 (26.56)	50.33 (77.65)	0.00

Notes: Mean and standard errors (in parentheses) by market type. P-values reported in column 3 are for mean in column 2 relative to the mean in column 1.

**Table A.3: Balance tests: Market participation by market type**

	(1) Secondary Market	(2) Central Market	(3) Diff.: p-value
Competition	0.13 (0.14)	0.13 (0.15)	0.48
Number of farmers	353.90 (383.54)	778.14 (711.57)	0.00
Number of traders	26.87 (28.45)	53.20 (74.70)	0.00

Notes: Mean and standard errors (in parentheses) by market type. P-values reported in column 3 are for mean in column 2 relative to the mean in column 1.

**Table A.4: Balance tests: Market participation by religious and rainfall events**

	Religious Day		Pre-week Rainfall		Market Day Rainfall	
	(1)	(2)	(3)	(4)	(5)	(6)
	Normal Day	Religious Day	Dry Week	Rain Week	Dry Day	Rain Day
Number of Farmers	664.89 (201.6)	181.45** (74.43)	691.61 (185.67)	499.76*** (184.67)	677.88 (210.92)	449.63* (229.25)
Number of Traders	40.97 (13.35)	-23.76 (18.60)	37.71 (13.34)	-31.21** (14.21)	38.38 (11.83)	-19.93 (19.32)

Notes: Regression estimates include market and time fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1 denote significant differences between market days.

**Table A.5: Farmers' price prediction by objective and subjective wheat quality**

	Price prediction			Total
	Accurate estimation	Underestimation	Overestimation	
<b>Objective quality</b>				
High %	40.4	8.6	51.0	100.0
Medium %	36.2	10.2	53.6	100.0
Low %	40.1	11.1	48.8	100.0
<b>Subjective quality</b>				
High %	53.5	11.5	35.0	100.0
Medium %	48.7	11.5	39.8	100.0
Low %	32.7	10.9	56.4	100.0

**Table A.6: Price premium for different quality attributes, with heterogeneity by marketing period**

	(1)	(2)	(3)	(4)	(5)	(6)
Quality variable:	Impurity	Moisture	Test-weight	Impurity	Moisture	Test-weight
Quality	0.02*** (0.01)	0.00 (0.02)	0.01 (0.04)	0.02*** (0.01)	-0.01 (0.03)	0.09 (0.12)
Follow-up	0.06** (0.03)	0.01 (0.09)	0.01 (0.01)			
Follow-up × Quality	-0.02 (0.01)	0.03 (0.03)	0.01 (0.09)			
Survey week				0.04 (0.03)	0.03 (0.03)	0.06 (0.06)
Survey week × Quality				-0.00 (0.00)	0.01 (0.01)	0.00 (0.01)
Constant	2.44*** (0.09)	2.40*** (0.10)	2.37*** (0.22)	2.29*** (0.14)	2.30*** (0.15)	1.85*** (0.66)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2725	2856	2731	2725	2856	2731
Number of clusters	30	30	30	30	30	30

Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. The impurity scale is reversed: high value is now purest wheat. Follow-up is a dummy equal to 1 if farmer *i* was surveyed during the second round. Survey week is the the week number since the opening of market *j* in which farmer *i* was surveyed. The quality term in the interaction variable corresponds to the quality attribute specified at the top of the column. Controls included: age of farmer *i*, gender of farmer *i*, yearly wheat production of farmer *i*, plot size of farmer *i*, travel time of farmer *i* to market *j*, type of wheat produced by farmer *i*, quantity sold by farmer *i*, and market day volume traded on market *j*. Standard errors (in parentheses) are clustered at the *woreda* level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

**Table A.7: Price premium for different quality attributes: covariates selection using a post double LASSO procedure**

	(1)	(2)	(3)
<b>Quality variable:</b>	Impurity	Moisture	Test-weight
Quality	0.02*** (0.01)	0.02 (0.01)	0.01 (0.03)
Constant	2.64*** (0.03)	2.55*** (0.04)	2.57*** (0.12)
Control	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Market FE	Yes	Yes	Yes
N	2683	2814	2689
Number of clusters	30	30	30

Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. The impurity scale is reversed: high value is now purest wheat. Relationship is a dummy equal to 1 if farmer  $i$  is engaged in a long-term relationship with a trader. Millers is a dummy equal to 1 if at least one miller is present near the market. Cooperatives is a dummy equal to 1 if at least one cooperative is present on market. Standard errors (in parentheses) are clustered at the *woreda* level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table A.8: Prediction (out-of-sample) accuracy for wheat price**

Models	Accuracy		
	RMSE		$R^2$
	Mean	CI	
Random Forest	0.75	[0.74,0.79]	0.88
eXtrem Gradient Boosting	0.76	[0.75,0.76]	0.88

Notes: RMSE is the out-of-sample root mean-squared error computed using the out-of-sample over five-fold estimations. Bootstrapped 95% confidence intervals for hold-out prediction performance are in brackets.  $R^2$  is the squared correlation between the predicted price and actual price in the hold-out sample.

**Table A.9: Price premium for different quality attributes, with heterogeneity by market rank: covariates selection using a post double LASSO procedure**

	(1)	(2)	(3)
Quality variable:	Impurity	Moisture	Test-weight
Quality	0.02*** (0.01)	0.04 (0.03)	-0.01 (0.02)
District Market × Quality	0.01 (0.01)	-0.03 (0.03)	0.10* (0.05)
Constant	2.50*** (0.02)	2.60*** (0.05)	2.23*** (0.20)
Control	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Market FE	Yes	Yes	Yes
N	2683	2814	2689
Number of clusters	30	30	30

Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. The impurity scale is reversed: high value is now purest wheat. Relationship is a dummy equal to 1 if farmer *i* is engaged in a long-term relationship with a trader. Millers is a dummy equal to 1 if at least one miller is present near the market. Cooperatives is a dummy equal to 1 if at least one cooperative is present near the market. Standard errors (in parentheses) are clustered at the *woreda* level. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**Table A.10: Price premium for different quality attributes, with heterogeneity by alternatives to market: covariates selection using a post double LASSO procedure**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quality variable:	Impurity	Moisture	Test-weight	Impurity	Moisture	Test-weight	Impurity	Moisture	Test-weight
Quality	0.02*** (0.01)	0.05** (0.02)	-0.00 (0.03)	0.01*** (0.01)	0.05* (0.03)	-0.002 (0.02)	0.01 (0.01)	-0.02 (0.02)	-0.01 (0.02)
Relationship	-0.01 (0.01)	0.11* (0.05)	-0.21 (0.21)						
Relationship × Quality	-0.01 (0.01)	-0.04* (0.02)	0.05 (0.05)						
Millers × Quality				0.00 (0.01)	-0.04 (0.04)	0.10** (0.04)			
Cooperatives × Quality							0.02*** (0.01)	0.08** (0.04)	0.08** (0.04)
Constant	2.58*** (0.03)	2.45*** (0.06)	2.56*** (0.14)	2.64*** (0.03)	2.49*** (0.06)	2.69*** (0.10)	2.48*** (0.02)	2.47*** (0.04)	2.49*** (0.10)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2683	2814	2689	2683	2814	2689	2683	2814	2689
Number of clusters	30	30	30	30	30	30	30	30	30

Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. The impurity scale is reversed: high value is now purest wheat. Relationship is a dummy equal to 1 if farmer *i* is engaged in a long-term relationship with a trader. Millers is a dummy equal to 1 if at least one miller is present near the market. Cooperatives is a dummy equal to 1 if at least one cooperative is present near the market. Standard errors (in parentheses) are clustered at the *woreda* level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## B. SURVEYS

**Figure B.1: Growers baseline survey**

### 2019 WHEAT GROWER BASELINE MARKET SURVEY

*University of California Berkeley*

#### SURVEY TO BE ADMINISTERED TO FARMERS THAT ENTER THE MARKET

	<i>Name</i>	<i>Code</i>
<i>Region</i>		
<i>Zone</i>		
<i>Woreda</i>		
<i>Kebele</i>		
<i>Market</i>		
<i>Date (day/month/year):</i> _____/_____/_____ _____		

#### A. At entry in the market *Time of*

*entry:*

*Is the farmer willing to participate? 1. Yes 2. No*

Name of farmer: \_\_\_\_\_

Mobile phone number: \_\_\_\_\_

*(record relatives/neighbors mobile phone number of the farmer don't have phone)*

Landline phone number: \_\_\_\_\_

*ONLY if the farmer has not provided a mobile number, record a landline number where he can be reached)*

Gender: \_\_\_\_\_ 1. Male \_\_\_\_\_ 2. Female

Age: \_\_\_\_\_ (in completed years)

Name of village where farmer lives \_\_\_\_\_ Village ID: \_\_\_\_\_

Distance from this village to the market \_\_\_\_\_ (in kms)

Name of development group: \_\_\_\_\_

1. What type of wheat do you produce? 1. Bread 2. Durum
2. What is the total area of wheat you have planted this year? (in ha) \_\_\_\_\_
3. How much is the total wheat you have produced this year? \_\_\_\_\_ kg
4. What quantity approximately do you have to sell today? \_\_\_\_\_ kg
5. Do you have a durable relationship with a trader? 1. Yes 2. No
6. At what price do you expect you could sell your wheat? \_\_\_\_\_ birr/kg
7. Suppose the price that the trader offers you is much smaller. Would you sell it anyway? 1. Yes 2. No
8. What is the minimum price you would accept for your wheat today? \_\_\_\_\_ birr/kg

*Thank you. I will let you go to the market now. On your way back, could you please stop again and let me know the actual weight and price you will have obtained for your wheat? I will then transfer 25 Birr on your cell phone (or give you 25 birr in cash) in gratitude for participating in the survey*

#### B. When returning from the market

9. Have you sold your wheat? 1. Yes 2. No
10. If no, why not? 1. Low/unattractive price 2. No wheat buyer 3. Change my mind
11. What was the weight of wheat that you sold? \_\_\_\_\_ kg
12. At what price did you sell it? \_\_\_\_\_ birr/kg
13. Have you sold your wheat to your usual trader(s)? 1. Yes 2. No If no why?
14. If no, why not? 1. Lower price 2. Underestimate weight 3. Unavailable 4. Contract/deal with another trader
15. How many traders did you consult before selling your wheat? \_\_\_\_\_ (Number of traders)

*Enumerator: Transfer 25 Birr to farmers cell phone or provide in cash if the farmer doesn't have a cell*

**Figure B.2: Grower’s midline survey**

**2020 WHEAT GROWER MIDLINE AND ENDLINE MARKET SURVEY**

*University of California Berkeley*

**8.1 SURVEY TO BE ADMINISTERED TO FARMERS THAT ENTER THE MARKET**

	Name	Code
Region		
Zone		
Woreda		
Kebele		
Market		

Date (day/month/year):  
 \_\_\_\_\_ / \_\_\_\_\_ / \_\_\_\_\_

**A. At entry in the market** *Time of entry:*

*Is the farmer willing to participate? 1. Yes 2. No*

Name of farmer: \_\_\_\_\_

Mobile phone number: \_\_\_\_\_

*(record relatives/neighbors mobile phone number of the farmer don't have phone)*

Landline phone number: \_\_\_\_\_

*ONLY if the farmer has not provided a mobile number, record a landline number where he can be reached)*

Gender: 1. Male 2. Female

Age: \_\_\_\_\_ (in completed years)

Name of village where farmer lives \_\_\_\_\_

Distance from this village to the market \_\_\_\_\_ (in kms)

Name of development group: \_\_\_\_\_

1. What type of wheat do you produce? 1. Bread 2. Durum
2. What is the total area of wheat you have planted this year? (in ha) \_\_\_\_\_
3. How much is the total wheat you have produced this year? \_\_\_\_\_ kg
4. What quantity approximately do you have to sell today? \_\_\_\_\_ kg
5. Do you have a durable relationship with a trader? 1. Yes 2. No
6. At what price do you expect you could sell your wheat? \_\_\_\_\_ birr/kg
7. How do you set your expected price? 1. Based on price info I gather from friends/neighbor 2. Based on price information I gather from traders 3. Based on price info I gather from gov't and non-gov't bodies 4. Based on last couple of weeks price 5. It is a mere guess
8. Suppose the price that the trader offers you is much smaller. Would you sell it anyway? 1. Yes 2. No
9. What is the minimum price you would accept for your wheat today? \_\_\_\_\_ birr/kg
10. What do you think about the quality of your wheat (considering grain size, impurity, hardness and its moisture)? **1. HIGH 2. Medium 3. LOW**
11. Are you aware that you can get your wheat certified on the market? 1. Yes, I watched a video about it 2. Yes, I saw it in the market 3. Yes, someone told me 4. No

*Thank you. I will let you go to the market now. On your way back, could you please stop again and let me know the actual weight and price you will have obtained for your wheat? I will then transfer 25 Birr on your cell phone (or give you 25 birr in cash) in gratitude for participating in the survey and additional 15 birr for the 1 kg sample wheat we took for further analysis.*

**Figure B.3: Market Day survey**

**2020 WHEAT GROWER MIDLINE MARKET SURVEY**

*University of California Berkeley*

**8.2 MARKET LEVEL SURVEY**

	<i>Name</i>	<i>Code</i>
<i>Region</i>		
<i>Zone</i>		
<i>Woreda</i>		
<i>Kebele</i>		
<i>Market</i>		

Date (day/month/year):

**A. General characteristics about the market day**

1. Opening hours: from    h    to    h
2. Weather: 1.No rain 2.Rain
3. Is it a religious day or public holiday? 1. Yes 2. No
4. Any other observation/major event on this market day?
  - a. If yes, please briefly describe
5. On which month the wheat marketing season start and end? a. Starting week/month:    /    b. End week/month    /    [use month codes]

**B. Market characteristics**

6. Is the market a district (woreda) level market? 1. Yes 2. No
7. Where specifically is the market located? 1. Inside the town 2. At the periphery of the town 3. Away from the town
8. Is there a price information board on the market? 1. Yes 2. No
  - a. If yes, does it contain information on wheat prices? 1. Yes 2.No
  - b. What does it say about wheat prices?
9. How many villages supply wheat to this market?            (number)
10. How often does the market operate? 1. Every day 2. Every 2-4 days 3. Every week 4. Every two weeks 5. Monthly
11. Total number of entrances to the market:            (number)
12. Number of entrances to the grain market section:            (number)
13. Estimated number farmers who come to sell grains:            (number)
14. Estimated number of farmers who come to sell wheat:            (number)
15. What percent of the wheat farmers enter through the two main entrances used for data collection?            (%)
16. Estimated number of total grain traders in the market: (a) resident        (number); (b) itinerant        (number)
17. Estimated number of grain traders that buy wheat: (a) resident        (number); (b) itinerant        (number)
18. Is license required to become a grain trader 1.Yes 2. No
19. If yes, how much is the cost of getting a license for grain trading?            (birr)
20. How much is the average wheat price per kilogram today (for average quality)?            (birr/kg)

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