Returns to Quality in Rural Agricultural Markets: Evidence from Wheat Markets in Ethiopia

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Abstract

In many Sub-Saharan countries, local farmers remain unable to meet the growing needs of local urban demand for higher-quality products, leading to a growing dependency on imports. While the literature has focused on production-side constraints to enhancing smallholder farmers' output quality, there is few evidence on market-side constraints. Using a unique sample of 3485 wheat farmers in Ethiopia, I examine the relationship between price obtained by farmers and quality supplied. Using objective and precise measures of observable (impurity content) and unobservable (flour-extraction rate and moisture level) quality attributes, I find no evidence of correlation with one-another, suggesting that observable attributes cannot serve as proxies for unobservable ones. This is further evidenced by transaction prices, showing that on average, markets only rewards those quality attributes that are observable at no cost. These results however hide cross-market heterogeneity. Observable quality attributes are better rewarded in larger and more competitive markets, while unobservable attributes benefit from the presence of grain millers and/or farmer cooperatives on market site. Theses results are supported by both regression and machine learning approaches.

Keywords: Crops Quality; Markets Incentives; Agriculture; Africa

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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 producers are often unable to supply the kind of higher-quality products increasingly demanded by a growing urban population, causing further dependency on imports. A large body of literature has focused on production-side constraints to enhancing the quality of food production in low-income countries. As for other agricultural technologies and practices, improving smallholder farmers' output quality can be constrained 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 an output markets perspective—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 to higher quality output depends on the extent to which quality is easily and unambiguously observable. Many attributes define an agricultural product's quality. Some are directly 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 both types of quality features are strongly correlated, farmers may rely on observable quality to obtain rewards for their investments in enhancing the unobserved quality of their product. When the correlation is weak one needs to further invest in the recognition of unobservable quality. Using a simple model, Fafchamps et al. (2008) shows that costly measures of unobservable quality attributes result in lower price premium for these attributes and lower investments by farmers towards enhancing these features in their products.

In this paper, I provide some of the first empirical evidence of the relationship between both observable and unobservable quality attributes and market price in rural markets of Sub-Saharan Africa where quality certification bodies are mostly unavailable to smallholder farmers (Abate et al., 2021). I rely on a unique set of data covering 3485 farmers in 60 rural wheat markets in Ethiopia, collected during the 2019-2020 marketing season. For each farmer, we obtained farmers' subjective measures of overall quality level (i.e., high, medium and low grade) alongside with price expectation upon entering the market and price obtained after the transaction was completed. We 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.[1] I use these measures to compute both objective measures of overall quality (i.e., high, medium and low grade) as well as measures of each quality attribute independently.

Results show a clear positive relationship between price obtained and overall quality. Results hold whether one uses objective or subjective measures of quality, suggesting that farmers are well aware of the overall quality of their product. In my preferred specification, I find a 2 to 8 percent price prime premium for higher overall quality of wheat. Turning to quality attributes separately, I find no correlation with one-another. Further, while there is a clear positive relationship between price and observable quality of wheat (10 percent purer wheat is paid 20 percent more), I find no relationship with unobservable attributes (i.e., moisture and flour-extraction rate) despite significant heterogeneity across farmers and their key importance to millers downstream the value chain.

Next I extend the model proposed in Fafchamps et al. (2008) to account for varying market conditions that may 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, 2010a, Casaburi et al., 2013), experience unequal levels of competition (Bergquist and Dinerstein, 2020, Macchiavello and Morjaria, 2021) and limited access to infrastructures (De Janvry and Sadoulet, 2020). Extension of Fafchamps et al. (2008) implies that favorable market conditions such as market size, competition level, and market infrastructures decreases the costs of measuring quality attributes, and as a result increase price premium for unobservable quality.

I test for these predictions along three market-level characteristics: market type (i.e., central district market versus secondary market), market day competition (i.e., number of traders per farmer), and market infrastructure (i.e., presence of cooperatives and milling plant). Results point to positive price premium on observable quality in central district markets. Although higher competition is associated with higher premium for unobservable quality, the relationship disappears in a two stage least square estimate where daily competition level is instrumented by local rainfall (Asfaw et al., 2010) and religious days calendar (Prunier, 2015). With respect to market infrastructures, presence of a milling plant is positively related to price premiums of unobservable attributes, while that of a cooperative is associated with higher prices for both observable and unobservable attributes. These results are largely confirmed using a machine learning approach testing which market conditions and farmers' characteristics bear the most power in price prediction. At market-level, this data-driven approach identifies volume traded, distance to the capital city (Addis Ababa) and competition, as the most important characteristics to explain overall price differences, while quality attributes are the strongest farmer-level predictor of price differences across farmers of a locality.

Together, these results provide three main contributions to the literature. First, I provide empirical

[1] Moisture content can be partly—though imprecisely—assessed by breaking wheat kernels.

evidence about quality recognition in developing countries' agricultural markets. Existing work suggests that high transaction costs prevent price premium 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 damages or grain size (Fafchamps et al., 2008, Jano and Hueth, 2014, 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, I also provide evidence that farmers are somewhat but only partially informed about the quality of the output they supply (Anissa et al., 2021, Kadjo et al., 2016).

Second, I contribute to an emerging body of literature on the role of locally-specific market conditions in transactions. Limited access to information, insufficient infrastructure and local institutional arrangements constraints farmers' ability to exploit market's opportunities (Aker, 2010a, Bergquist and Dinerstein, 2020, Casaburi and Reed, 2019, Deutschmann et al., 2020). Low market competition, particularly by limiting outside option for farmers and increasing traders' market power, can reduce market price and returns to supply high-quality outputs. Nevertheless, previous works on quality recognition have left aside market conditions from their settings (Fafchamps et al., 2008, Kadjo et al., 2016, Magnan et al., 2021). This paper adds to this literature by studying the interaction between specific market conditions and price premium for unobservable and observable attributes. In particular, I find that price premium varies across competition level only for observable attributes at no or small costs.

Third, I provide evidence about the farmer-level demand-side constraints in agricultural quality upgrading. Policies have so far mostly concentrated on alleviating supply-side constraints to enhance quality, 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 a clear recognition of quality in local markets, 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 adopt a demand-side approach and assume that improving quality recognition by local traders will encourage farmers' supply of higher-quality products (Abate and Bernard, 2017, Bernard et al., 2017, Bold et al., 2021, Deutschmann et al., 2020). In a recent randomized controlled study in the Senegalese onion value chain, Bernard et al. (2017) highlight the importance of farmers' expectation regarding market conditions on quality-enhancing inputs investments. More precisely, they show that supply-side constraints are unlikely to explain the low-quality supply, while uncertainty about markets rewards for quality onions is a significant impediment to quality supply. They provide evidence that producers' awareness of changes in locally-specific market conditions lead to important and rapid farmers' response, inducing the delivery of higher-quality crops. My results add to this literature, through further description on the role of market conditions onto price-premium, distinguishing between observable and unobservable quality attributes.

The remainder of the paper is organized as follows. In Section 2, I provide additional background information about 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 covariates and outcomes of interest. The conceptual framework is outlined in Section 5, and Section 6 presents the empirical strategy. 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 a source of income for farmers. Wheat is grown mainly in central and southern highlands by 5 million smallholder farmers and occupies more than 20% of cereals cultivated areas (Minot et al., 2019, Shiferaw et al., 2014).[2] National wheat processing industry demand is growing and driven by urban growth that reshapes food preferences towards processed staple foods (Worku et al., 2017). This demand is increasingly satisfied by imports, now representing almost one-third of domestic consumption. Despite significant investments and policies to increase local agricultural supply 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 supply by smallholders are key factors that inhibit the development of the Ethiopian wheat value chain (Gebreselassie et al., 2017). Smallholder farmers have a limited access to modern production inputs such as fertilizer or improved seeds and technology due to incomplete credit markets, ineffective agricultural extension service, or climatic shocks (Dercon and Christiaensen, 2011). For instance, although wheat is a rain-fed crop, less than one percent of the wheat area is irrigated, making it vulnerable to climatic hazard (Seyoum Taffesse et al., 2012).[3] Insufficient infrastructures (e.g., limited road networks, deficiency market information, restricted access to internet and phone networks) increase transaction costs, price volatility, and reduce market integration, thereby narrowing farmers' participation to the Ethiopian wheat market (Minot et al., 2019). More recently, Ethiopia's agricultural strategy led by the Federal Government of Ethiopia involves a transition towards smallholder farmers inclusion and value chain development (Dercon et al., 2019, Tadesse et al., 2018). Among several objectives, a key ambition is to promote the production of high-quality wheat to reach self-sufficiency.

Ethiopa's wheat supply chains rests on a large and mostly uncoordinated network of rural middlemen (i.e., traders, wholesalers, or brokers) whose influence in the wheat value chain increased since

[2] A smallholder is a farming household with a plot smaller than two hectares.

[3] There are two rainy seasons: (i) the short rainy season (*Belg*) occurs between March and May while (ii) the long rainy season (*Meher*) between June and September.

the fall of the Derg Regime in 1991 (Azam, 1993, Dercon, 1995, Gabre-Madhin and Goggin, 2005, Gebreselassie et al., 2017).[4] Today, middlemen represent the main wheat buyers on local markets and ensure the transportation from production areas (i.e., Amhara and Oromia) to demand places (i.e., Addis Ababa or Dire Dawa) and downstream actors like millers. [5]. It is often argued that middlemen use their dominant position and informational advantages over farmers to impose their condition on the market (Osborne, 2005)

Formal systems of grade and standards exist for many crops in Ethiopia and for wheat in particular. Quality assessment and certification are however limited to large (often imported) consignments and are of limited use to smallholder farmers given their small transaction size (typically 200kg), and comparatively large fixed-costs involved in quality assessment (Abate and Bernard, 2017, Abate et al., 2021, Anissa et al., 2021). Hence, price bargaining on spot market is limited to weight and observable attributes (i.e., color, kernel size, foreign matters). As described in Abate and Bernard (2017), traders do not bargain on unobservable quality attribute (i.e., flour-extraction rate). As quality is not rewarded, farmers can only increase their income by providing larger volumes. Traders aggregate and mix individual farmers' supply and sell the aggregate output to a downstream actor (e.g., millers, pasta factory, larger traders).

3 Research Design and data sources

3.1. Sample selection and survey

I rely on data that we 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 regions (Figure A.2)[6]. In the 2018-2019 marketing season we conducted a census of all wheat markets in the regions, for which we collected market-level information such as the estimated number of actors, the volume traded, season length, and market facilities. From this census, we selected a sample of 60 markets in 30 *woreda* (i.e., district). More precisely, we sampled 2 markets per *woreda*: the main wheat market and a secondary one. The main wheat market corresponds to the principal market in the *woreda* in terms of volume trade, number of participants. The secondary market was selected within 30km from the main market. It operates during the same months of the year, but usually operates on a different week day.

In each market, and for two survey rounds, we collected information from 30 randomly selected

[4] 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 involved the abolition of these quota systems.

[5] See Figure A.1 for a detailed map of production and market flows.

[6] This 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.

wheat farmers who were present on the market to sell wheat on the day of the survey. Two enumerators were posted at the two main market access roads and surveyed a randomly selected wheat farmer every 10 minutes among those entering the market. The first round of survey was conducted in December 2019 and January 2020 and the second one in March 2020, early in the wheat marketing season and at peak supply time, respectively (Figure A.3). Our final sample includes 3584 farmers, 1790 for the first survey round, and 1694 for the second one.[7]

On a given day, farmers were interviewed twice: upon entering the market and upon leaving it (Figure B.1). In the first part, we collected information on farmers' characteristics (e.g., age, gender, travel time), production performance (e.g., wheat plot area, volume produced), expected price, and self-assessed quality of their wheat (only in the March 2020 survey). Then, enumerators purchased a 1 kg sample of farmers' wheat to be later analyzed. Farmers were then told that they would be paid 25 Birr (i.e., 0.65 U.S. dollar) if they came back to answer another set of questions upon leaving the market. In this second part, we collected information on the wheat transactions that they conducted that day, including price per kg and quantity sold.

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

3.2. Quality measures

We define two categories of aggregate quality measures: (i) subjective and (ii) objective. Subjective measure consists in individual perceptions on the quality products. This measure is mostly based on visual inspection and experience. Subjective measures are usually considered inaccurate, but absent objective ones, they are the ones driving 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 mostly 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.

Our data enables me to combine the two approaches. First, our subjective measure is farmers self-assessment of the quality of the wheat they supply. Farmers classified their wheat on a three grade scale (i.e., low, medium, high). Second, using the 1 kg wheat sample bought to farmers, we objectively measured three quality attributes:

1. **Moisture rate** assesses the water content in the wheat kernel, which affects the seed quality and storage life. Weather conditions during the growing season as well as storage condition after

[7] Note that while the same markets were surveyed twice, different farmers were interviewed across the two survey rounds. We surveyed only 58 markets during the second survey round due to the COVID-19 pandemic.

harvest affect moisture content. High moisture content decreases the grain protein content, while low moisture content results in a hard grain with low flour yield.

2. **Test-weight** is a measure of 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 and results in a higher flour yield.

3. **Impurity rate** is the share of foreign matter such as stone, other cereals, or cobs in the sample. Low impurity guarantees that the grain is whole in volume and free of foreign elements. We use a grain sieve to separate foreign matter from a 100g sample wheat analyzed. We then weight the residues, which gives us the impurity rate.

It is important to note that I define moisture and extraction rate as unobservable attributes because they are not readily observable to the naked eyes, whereas impurity is fully observable. Each of these dimensions is graded on a three-point scale based on the government's official grading system. Then, an aggregate grade (i.e., low, medium, high) is computed using the lowest factor approach.[8]

3.3. Additional Data Sources

3.3.1. Precipitation Data

I rely on Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) daily rainfall estimates as a source of precipitation data set. Analyses of climate variability require consistent rainfall time series at high temporal and spatial resolutions. Sparse or non-existent ground weather stations in developing countries induce growing utilization 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 more accurate in Ethiopia (and in Eastern Africa) despite a decline in accuracy in mountainous or coastal areas. I collect precipitation data at the market level for the study period (December 2019 to March 2020). I then identify (i) wet market day and, (ii) market days for which rainfall were important (i.e., higher than 10mm) in the previous 7 days.

3.3.2. Population density data

I assess population density in the *Kebele* (i.e., village) where the market is located. *Kebele* is the smallest administrative unit, the main advantage to use it is that each market is localized in a distinct *Kebele*. Thus, I have a specific measure of population density for each market. To build population

[8] Quality grade corresponds to the lowest standard grade in the considered dimensions.

density estimates, I use buildings recorded in Facebook's Data for Good program (Facebook, 2021). The main advantage of this data over other available high-resolution datasets of populated areas such as Open Street Maps, is that it covers the whole study region consistently. The map is built by training a neural network algorithm on houses satellite images. The primary output is a map of 30-meter spatial resolution showing for each pixel whether at least one house was found (example in Figure A.4). Then, the obtained map is combined with available census data and other population datasets to provides population estimates within the selected area. This approach for house detection has been assessed and found accurate in Malawi by Kilic et al. (2016). Table 1 presents summary statistics from this data.

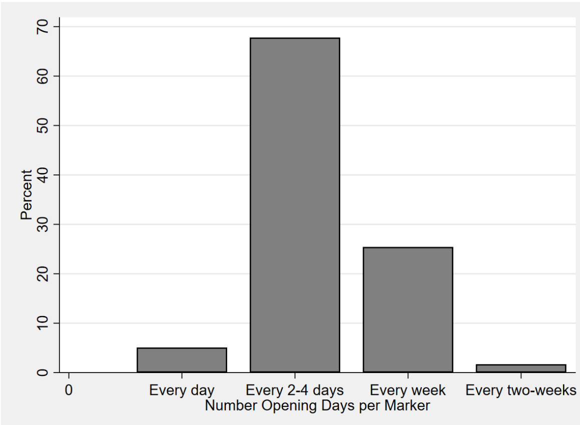
4 Descriptive evidence

The following part of this paper moves on to describe in greater detail the main characteristics of the market environment and the farmers. Additionally, I provide descriptive statistics and information about the principal outcomes of interest, namely grain quality and price.

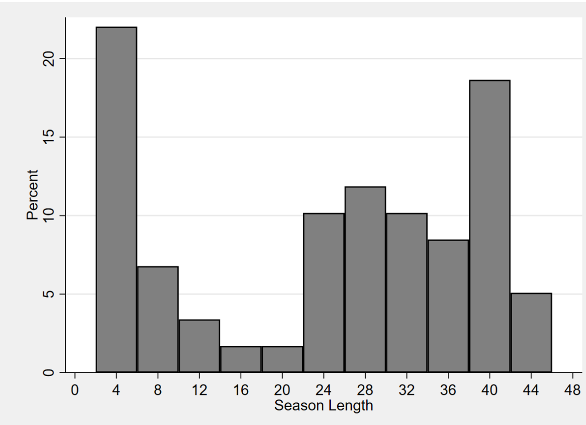
4.1. Open air rural wheat markets

This study takes place in open air markets in which smallholder farmers sell their products, mostly to traders. These markets usually occur on a predetermined day of the week, throughout the wheat marketing season (Figure 1a). When they occur on more than one day a week, there are typically a main market day and secondary market days. Importantly, the start of the marketing season varies according to the agroecological conditions, from October to January, and ends when the long rainy season occurs in June or July. Figure 1b presents the distribution of the season length per market, which varies from 4 to 44 weeks with a mean of 24 weeks.

Figure 1: Number of opening days and season length per market



(a) Number of opening days each week per market



(b) Season Length in week per Market

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

In Table 1 I present a set of summary statistics on market characteristics and market day condition. The top panel displays time-invariant market characteristics such as price information board, presence of millers or cooperatives, length of the season, and market location at the 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. First, it exhibits time-invariant market characteristics such as market facilities available Moreover, it displays market day-related variables and among these the number of traders and farmers on the market day

Market conditions are heterogeneous. Only a single market possesses a price information board, but it does not provide wheat prices. As in Bernard et al. (2013), I find an unequal distribution of cooperatives across markets: 60 percent of farmers have access to a market with a cooperative, and while millers are major wheat value-chain actors, only 54 percent of farmers sell wheat on market with or close to a miller plant.

On average, a market day gathers 560 farmers from nearby localities, and 40 traders. I use the ratio of the number of farmers per trader as my main indicator of competition.[9] On average there are 13 traders per 100 farmers on a given market day albeit with significant heterogeneity. Figure 2a displays the distribution of competition on given market days distinguishing between main and secondary markets. The distribution is skewed to the left—lower number of traders per farmers. I find no clear difference in competition across main and secondary markets, despite significant differences in the number of farmers and traders across market types (Figure A.6). This is confirmed by formal tests presented in Table A.3. Finally, both the numbers of farmers and traders are smaller when market

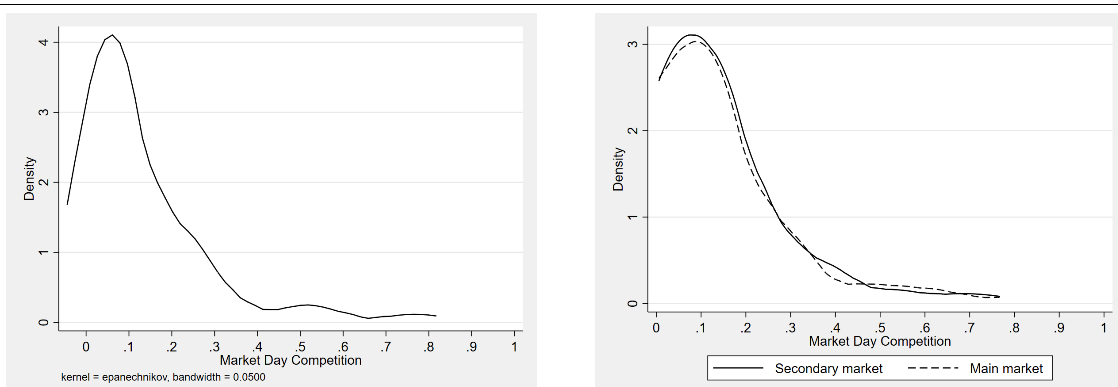
[9]To facilitate interpretation I rescale the variable by multiplying by 100.

day occurs on a religious day, and one finds that the competition level is slightly higher on that day (Table A.4).

Table 1: Market characteristics

	Mean	SD	N
Top Panel: time-invariant market characteristics			
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^2)	1,876	2,442.75	60
Bottom Panel: market-day specifities			
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

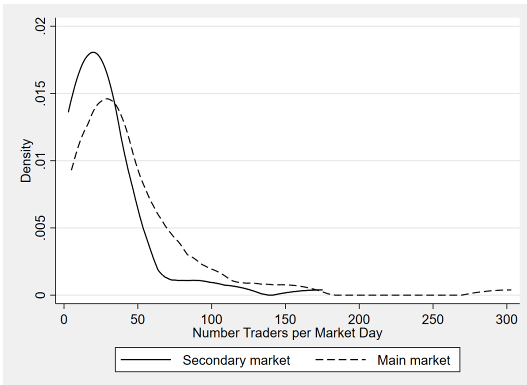
Figure 2: Market Day Competition in all markets and by market type



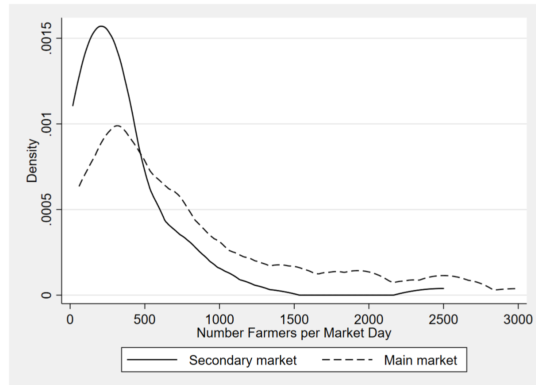
(a) Market Day Competition in all markets **(b)** Market Day Competition by market type

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

Figure 3: Number of traders and farmers on market day by market type



(a) Number of traders by market type



(b) Number of farmers by market type

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

4.2. Smallholder farmers

Our sample is mostly composed of small-scale wheat producers (Table 2) with an average 0.98 Ha of cultivated wheat, and an average production of 2.7 tons. These findings are similar to the results observed by Minot et al. (2019) in their detailed analysis of the Ethiopian wheat supply chain. Yields per hectare are particularly low in comparison with most productive countries at both continental and world level. Smallholders farmers are mainly located in isolated areas and spend close to one hour to reach the marketplace. Transactions are small: half of the farmers supply less than 50kg of wheat, which corresponds to one standardized bag. Lastly, as the Ethiopian wheat market is characterized by high transaction costs, no formal contract, lack of formal institution, more than half of the farmers are involved in a long-term relationship with traders.

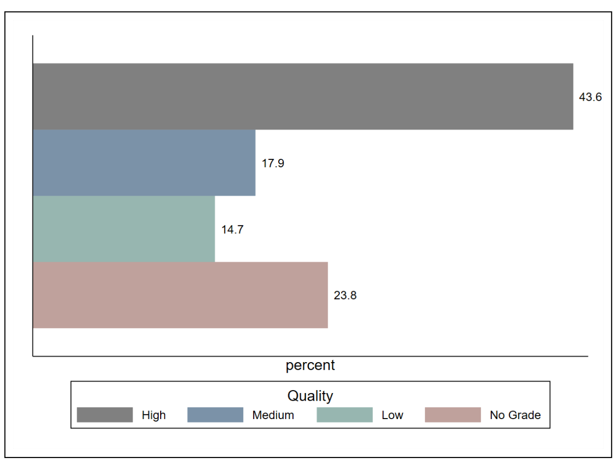
Table 2: Farmers characteristics

	Mean	SD	N
Farmers characteristics			
Age	36.37	13.58	3,484
Female (0/1)	.46	.49	3,484
Travel time (min)	58.01	46.14	3,483
Agriculture variables			
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
Objective quality			
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 described above in Section 3, we collected samples from farmers on market day and tested them for test-weight, moisture and impurity content to obtain objective quality measures. Considering the overall grade. Figure 4 shows that 43 percent of the wheat sample is measured as high quality whereas almost 40 percent is at most of low quality (including low quality and no-grade together). I do not find evidence of quality-related time arbitrage (Kadjo et al., 2016), as the distribution of quality is consistent across the two survey period (peak supply time and end of marketing season)—Figure A.7.

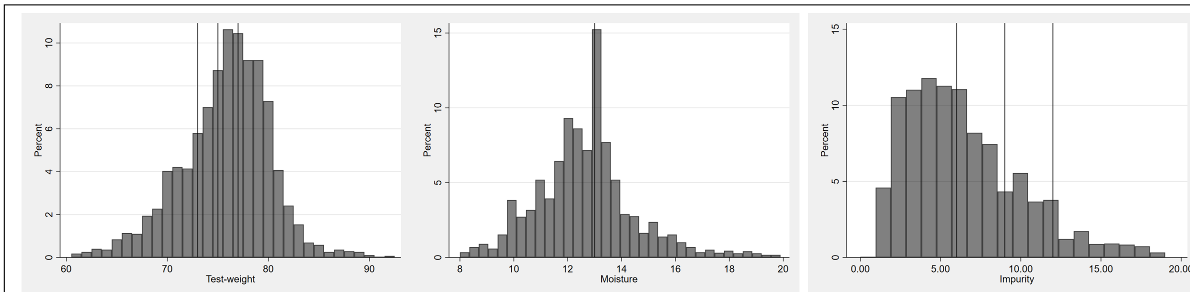
Figure 4: Quality distribution



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

Turning to each quality attribute separately, Figure 5 displays their distribution in the sample. As discussed in Section 3, test-weight and moisture are unobservable attributes, while impurity content is an observable attribute.[10] Accordingly, one observes a larger distribution of unobservable attributes (5a and 5b) compared to observable attribute (5c) across the different grades. For impurity, less than 1 percent of the wheat is not graded (i.e. below the low quality standard). In comparison, it reaches almost 20 percent 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 farmers' investments in inputs and practices. The differences may also reflect the absence of price premium for these unobservable dimensions, thereby limiting farmers' incentives to upgrade their quality in these dimensions.

Figure 5: Quality distribution by criteria



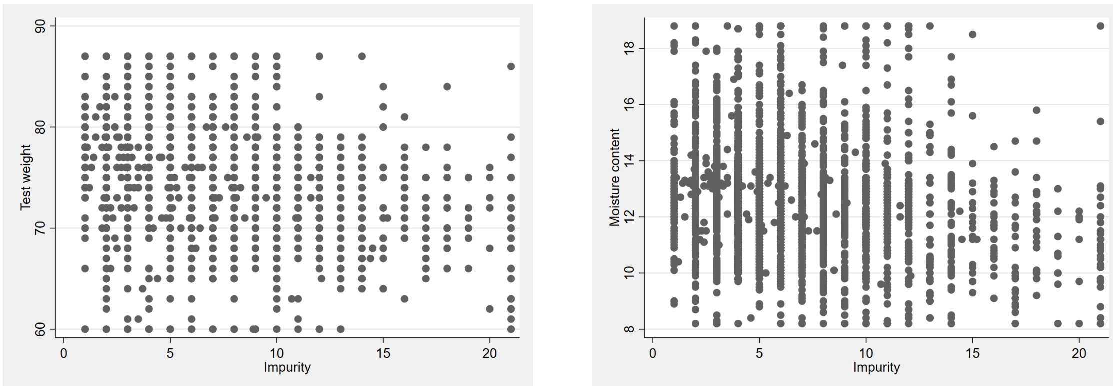
(a) Test-weight **(b)** Moisture content **(c)** Impurity content

Source: Author's computation based on 2019/2020 wheat growers' survey.
Notes: vertical lines represent the threshold for the different grade.
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.

In Figure 6, I investigate the correlation between observable (i.e., impurity) and unobservable (i.e., test-weight, moisture) quality attributes. A high correlation would imply that one relies on observable attributes to infer the level of unobserved ones (Barzel, 1982). However, one finds no clear relatinship in Figure 6, such that market actors cannot rely on impurity to estimate test-weight or moisture level.

[10]See Table A.1 for quality thresholds in each attributes

Figure 6: Relationship between unobservable and observable characteristics



(a) Test weight and Impurity content **(b)** Moisture content and Impurity content

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

Next, I consider farmers' own assessment of the quality of their product, a subjective quality measure, which I compare to the objective estimates. As presented in Table 3, only 28 percent of farmers accurately estimate the quality of their output, while 26 percent under-estimate it and 46 percent over-estimate it. Thus, an in line with Anissa et al. (2021), farmers are somewhat but only imperfectly aware about the quality of the wheat they supply. Two reasons may explain this gap. First, farmers rely on an incomplete vector of quality attributes composed mainly of observable ones for their predictions. Second, farmers perceived enumerators as government agents and overrated their products to satisfy them.[11]

Table 3: Farmers' quality prediction by subjective quality

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

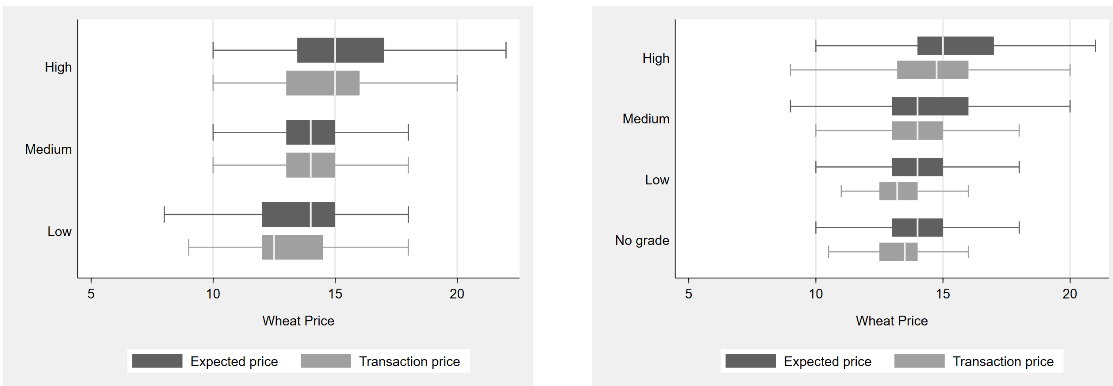
Source: Author's computation based on 2019/2020 wheat survey.

Last, I compare farmers' expected price and the effective market price they obtained, by categories objective and subjective quality. As shown in Figure 7, expected prices tend 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. Finally, the figure shows a greater price dispersion for objectively higher quality wheat

[11] In line with a Hawthorne effect.

than lower one. Further details on farmers' price prediction accuracy are presented in Table A.5, which shows that precision of price estimation is positively correlated with subjective grade but not with the objective one.

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



(a) Subjective quality **(b)** Objective quality

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

5 Conceptual framework

To support my empirical analysis on quality recognition in the agricultural market, I begin by following the model initially proposed by Lancaster (1966) and later extended by Fafchamps et al. (2008). I then extend this conceptual framework to include the heterogeneity of quality recognition across market conditions.

5.1. A model of quality

Following Fafchamps et al. (2008), I model utility as a function of characteristics of the staple crop, rather than as a function of the staple crop itself. Let $x_i = \{x_i^0, x_i^1, \ldots x_i^N\}$ be a vector of N quality attributes (e.g., foreign matter, moisture, color) in a staple crop i with x_i^k the level of attribute k in crop i. Consumption of attributes procure a positive utility for buyers (i.e., traders), denoted in normalized way such as: $U = U\{x_i^0, x_i^1, \ldots x_i^N\}$ with $\frac{\partial U}{\partial x_i^k} \geq 0$. I assume that U is expressed in monetary terms.

I consider an agricultural markets where two staple crops are supplied, i and j, strictly similar except in quantity of attribute k. I assume that all attributes are perfectly observable. The buyer is indifferent between crops when the difference in price is strictly equal to the difference in utility terms:

$$U(x_i^0, \ldots, x_i^k, \ldots x_i^N) - p_i = U(x_j^0, \ldots, \tilde{x}_j^k, \ldots x_j^N) - p_j$$
$$p_i - p_j = \frac{\partial U}{\partial x^k}(x_i^k - \tilde{x}_j^k)$$

The only difference between the two crops is k, thus the difference in price can be considered as the implicit price of attribute k.

I assume that farmers have identical joint production function:

$$F(x, z) \leq 0$$

where z is the vector of inputs and costs required to produce a vector of attributes x. Positive values of the production function correspond to inefficient combinations of inputs and outputs.

The efficient allocation is the solution to the following social planner problem:

$$\underset{(x,z)}{\text{Max}} \quad U(x^0, x^1, \ldots x^N) - \sum_{n=1}^{M} p_n z_n \tag{1}$$
$$\text{Subject to: } F(x_i^0, x_i^1, \ldots x_i^N; z_1, \ldots z_M) \leq 0$$

Such that at the optimum:

$$\frac{dp}{dx^k} = \frac{\partial U}{\partial x^k} = p\frac{\partial F}{\partial x^k} \tag{2}$$

Equation (2) means that, in an efficient equilibrium, the price premium related to attribute k is equal to the marginal utility of that attribute (in monetary terms) and also equal to the marginal cost of producing it. The relevance of this rather standard microeconomics results is that it pertains here to a certain attribute within a given product.

To reach the efficient equilibrium, correct information about attributes must be easily available on market. For instance, consider that information is available only for a subset of attributes S with $S < N$. As traders only pay for attributes on which information is available, the price of crop i will depends only on the subset of attributes: $\{x_i^0, x_i^1, \ldots x_i^S\}$. This reduces farmers' incentive to supply the crop with attributes for which information are not available (i.e., attributes out of S). As farmers do not provide additional effort to produce such attributes, they are set at the lowest level allowed by the production function F.

Proposition 1: *Traders will only pay for attributes for which information is available on the market.*

Given high transaction costs in local agricultural markets, obtaining information on attribute must be costly. If the attribute is not fully observable when the transaction occurs, it is impossible for traders to signal their willingness to pay more for high quality crop.

5.2. Observability degree and price premium

Based on Fafchamps et al. (2008), let a buyer considering whether to buy a staple crop and not buying it, result in a normalized payoff of 0. The staple crop i may contain a discrete attribute k: $x^k = \{0, 1\}$.

The presence of the attribute provides utility level U_1 for the buyer, and U_0 otherwise with $U_1 > U_0$. A staple crop with attribute k (i.e., $x^k = 1$) is sold at price p_1, or else at price p_0 , with $p_0 < p_1$. Hence, the quality price premium paid on market is defined as:

$$\alpha = p_1 - p_0$$

Some attributes are observed at no cost on market (i.e., search attribute) while other are observable at a cost supported by buyer (i.e., experience or credence attribute). However buyer have imperfect information about farmers' agricultural practices (e.g., seeds, fertilizer, land yields, crop management practices) which can affect the presence of the attribute q^k. Assume that when an attribute is not observable, a buyer either incurs additional costs c to measure the true value of attribute q^k, or accepts to support a quality uncertainty risk. If q^k is missing, the buyer gives p_0. When the buyer does not inspect, his expected payoff is $\pi^n = \rho U_1 + (1 - \rho)U_0 - p_1$, with ρ the degree of observability of the attribute q^k. Conversely, if the buyer inspects, his expected payoff is $\pi^i = \rho(U_1 - p_1 - c) + (1 - \rho)(U_0 - p_0 - c)$. Hence the gain resulting from quality assessment is:

$$G = \pi^i - \pi^n = \alpha(1 - \rho) - c \tag{3}$$

Equation (3) shows that the gain from quality assessment decreases with the degree of observability (ρ) and costs of quality measurement (c), and grows with the price premium (α). Then, if the attribute is observable to the naked eyes $G = -c$, the buyer does not pay to assess quality. In agricultural market, it is the case for some attribute such as size, color or impurity rate. For less observable attributes, the buyer inspects as long as the inspecting costs is smaller than the price premium: $G = \alpha - c$. The buyer is ready to pay as long as his expected utility for the attribute is higher than the cost of measuring quality.

Next, consider the farmer's incentives. As the buyer purchases the staple crop without the attribute as long as $U_0 \leq p_0$, the farmer has interest to set his effort level such as $p_0^* = U_0$. Considering now the staple food with the attribute, one can solve equation (3) for ρ in order to determine how much an attribute may be difficult to observe without inducing the buyer to incur quality measuring cost:

$$\rho^* = \frac{\alpha - c}{\alpha} \tag{4}$$

Let us now consider two specific cases, noting that the buyer buys the staple crop with the attribute if $\pi^n \geq 0$. In the first case, the cost of measuring quality is null. It follows that the buyer assess at no cost the quality for each transaction: $\rho^* = 1$. The price of the staple food with the attribute is given by:

$$\begin{aligned} \pi^n &= \rho U_1 + (1-\rho)U_0 - p_1 \\ &= U_1 - p_1 \end{aligned} \tag{5}$$

The higher price possible is $p_1^* = U_1\theta$, and efficiency is achieved because the equilibrium price premium $\alpha^* = p_1^* - p_0^*$ is equal to the utility gain provided by the attribute: $U_1 - U_0$. As a result, the farmer has incentives to supply its staple crop with this attribute as it is rewarded by buyers.

In the second case, the cost of measuring the attribute is high, so high that the buyer never does: $c > U_1 - U_0$. In a such situation, the buyer does not observe whether the attribute is present: $\rho^* = 0$ which yields to:

$$\begin{aligned} \pi^n &= \rho U_1 + (1-\rho)U_0 - p_1 \\ &= U_0 - p_1 \end{aligned} \tag{6}$$

Given that in equilibrium $U_0 = p_0$, it follows that the optimum price for staple crop with the attribute is now $p_1 = p_0$.

Last, let us consider an intermediate case, closer to reality. The equilibrium price premium is obtained by substituting $\pi^n = 0$ in equation (4) and using $U_0 = p_0$. It yields to:

$$\begin{aligned} \frac{\alpha - c}{\alpha}U_1 + (1 - \frac{\alpha - c}{\alpha})U_0 - p_1 = 0 \\ \frac{\alpha - c}{\alpha}U_1 + (1 - \frac{\alpha - c}{\alpha})U_0 - (U_0 + \alpha) = 0 \\ \alpha^2 - \alpha(U_1 - U_0) + c(U_1 - U_0) = 0 \end{aligned} \tag{7}$$

where for notation simplicity, $b = U_1 - U_0$. The optimal[12] root of equation (7) is :

$$\alpha^* = \frac{1}{2}(b + \sqrt{b(b - 4c)}) \tag{8}$$

Thus, $\alpha^* < (U_1 - U_0)$, except when $c = 0$, in which case $\alpha^* = (U_1 - U_0)$. Equation (8) highlights that the price paid for the staple crop with the attribute $p_1 = p_0 + \alpha^*$ shrinks with the increase in inspection costs c. This is because the fixed cost of measuring the attribute increases independently of transaction size, discouraging the buyer to support such cost.

Proposition 2: *For perfectly observable attribute, there is a price premium equal to its utility gain:* $\alpha = (U_1 - U_0)$. *The price premium shrinks as the observability of the attributes reduces (ρ) due to a rise in quality assessment cost (c). When the cost to assess an attribute is too high, there is not price premium.*

Proposition 2 shows that the presence of inspection cost to reveal the value of an attribute prevents market recognition for weakly observable attribute. For instance, when a attribute is fully unobservable, it will not be rewarded by traders and, as a result discourages farmers to supply it.

5.3. Market conditions and quality recognition

So far we discussed the cost of measuring attribute according to their degree of observability on homogeneous markets. I now extend the framework to consider heterogeneity in market conditions. Market conditions can be defined as any market characteristics which affects transaction cost such as competition, remoteness, presence of cooperatives and others. Market condition θ is continuous and normalized such as $\theta \in]0, 1]$. Costs to assess quality (c) decrease as the market conditions improve (i.e., $\theta \to 1$) and increases as market conditions worsen (i.e., $\theta \to 0$). Let the costs to assess quality be now denoted with $c = c^{1-\theta}$. This has no effect on price premium for perfect observable attribute as shown in equation (6). However, it does for weakly observable attributes. Then rewriting equation (8) with the new costs yields to:

$$\alpha^* = \frac{1}{2}(b + \sqrt{b(b - 4c^{1-\theta}}). \tag{9}$$

It is easy to verify that α^* decreases when market conditions are less profitable. Equation (9) shows that c falls with better market condition θ. The reason is that as market conditions improve, the trader has larger access to knowledge and information, and this reduces the transaction costs to measuring quality.

Proposition 3: *It is less expensive to assess unobservable quality attribute on better condition markets. As a result, the price premium for a given unobservable attribute will be higher on market with*

[12] The other root is always smaller and never an optimal choice for the farmer.

better conditions. For a high enough cost to measure a given attribute, the price premium associated is null on all markets.

6 Empirical strategy

Following the analytical framework above, I describe below the empirical strategy to estimating price returns to observable and unobservable quality across rural Ethiopian wheat markets.

6.1. Econometric approaches

I estimate the price-quality using the following equation based on ordinary least squares estimates:

$$ln(Y_{ijt}) = \beta_0 + \beta_1 Q_{ijt} + \beta_2 X_{ijt} + \beta_3 X'_{jt} + \gamma_j + \mu_t + \epsilon_{ijk} \tag{10}$$

where Y_{ijt} is the natural logarithm of wheat price per kg obtained by farmer i in market j at time t. Q_{ijt} represents wheat quality of farmer i in market j at time t. This variable may alternatively be the overall grade, or the measured quality level for each attribute separately. The variables X_{ijt} and X'_{jt} are vectors of farmer-level (i.e., age, gender, yearly wheat production, wheat plot area, travel time to market, quantity sold on market day) and market-level characteristics (i.e., overall volume traded) at time t. The terms γ_j and μ_t are market and time (i.e., survey week) fixed effects, respectively. The standard errors ϵ_{ijk} are clustered at the *woreda* level.[13] The primary null assumption to be tested is whether β_1 is zero: the price difference between different quality wheat.

I then consider whether quality recognition varies with market conditions. I use two measures of market condition: (i) the market type (i.e., district or secondary market) and (ii) the level of competition on market day. I estimate quality price premium heterogeneity by market conditions using the following equation:

$$ln(Y_{ijt}) = \beta_0 + \beta_1 Q_{ijt} + \beta_2 C_{jt} + \beta_3 (Q_{ijt} \times C_{jt}) + \beta_4 X_{ijt} + \beta_5 X'_{jt} + \gamma_j + \mu_t + \epsilon_{ijk} \tag{11}$$

where C_{jt} is the variable corresponding to the market condition j at period t. The primary null assumption to be tested is whether β_3 is zero: the effect of quality price premium depends on market conditions.

However, the market day competition is (quite plausibly) endogenous for at least two reasons. First, unobservable factors can affect both traders' and farmers' behavior and, thus, their market participation. Second, the relationship between competition and price may suffer from reverse causality bias. Indeed, markets are close within a *woreda* which can involve spatial arbitrage from actors in their

[13] Following recommendations from Abadie et al. (2017), I cluster standard-errors at *woreda* level as it corresponds to the sampling process level.

choice to participate in a given market. For instance, high-quality producing farmers can decide to sell their output on central markets to get a better price. Thus the exogeneity assumption $E\left[\epsilon_{ijk}|C_{jt}\right]=0$ is possibly violated.

To improve identification of the causal effects of market competition market price, I adopt a simple instrumental variable (IV) strategy. I rely on the occurrence of holy days on market day and rainfall during pre-week and market day as instruments for the market competition. Religions are embedded in Ethiopian society for centuries, religious days remain essentials and are celebrated by religious members (Prunier, 2015). Table A.4 shows that market participation is lower on religious day, which can in turn affect competition.

A recent literature is investigating the relationship between rainfall and agricultural market performance. Rainfall has several implications on farmers' participation in the market (Asfaw et al., 2010), on grain markets price (Aker, 2010b), and on volume traded due to poor road access (Salazar et al., 2019). Limited access to modern storage is another factor that maintains farmers dependent on weather conditions. Thus, precipitation increases rot risks for unstored crops and constraints farmers in their marketing decision.

I, therefore, use a two-stage least squares estimation where the market competition is instrumented by whether the market day occurs on a holy day, on a rainy day, and whether rainfall were higher than 10mm in the previous 7 days. Then, I estimate wheat price heterogeneity on the predicted value of market competition given by:

$$FirstStage: C_{jt}=\theta_0+\theta_1 Z_{jt}+\theta_2 X_{ijt}+\theta_3 X'_{jt}+\gamma_j+\mu_t+\phi_{ijk} \tag{12a}$$

$$SecondStage: ln(Y_{ijt})=\beta_1 Q_{ijt}+\beta_2 \hat{C}_{jt}+\beta_3(Q_{ijt}\times\hat{C}_{jt})+\beta_4 X_{ijt}+\beta_5 X'_{jt}+\gamma_j+\mu_t+\epsilon_{ijk} \tag{12b}$$

With Z_{jt} indicates the vector of instruments. In the second stage, I estimate the natural logarithm of wheat price per kg, $\ln(Y_{ijt})$, on the predicted value of competition ($\hat{C}_{jt}$) obtained from the first stage. The interaction term gives us the price premium heterogeneity by competition level.

6.2. Machine learning approaches

I extend my analysis of the quality-price relationship using a predictive model based on machine learning (ML) methods.[14] ML methods have advantages 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 pittfalls (Athey and Imbens, 2019, Mullainathan and Spiess, 2017). ML data-driven approaches do not rely on pre-specified parametric

[14] ML literature uses specific terminology. The sample used to estimate the parameters is the *training* sample. Instead of estimating a model, I *train* it. Covariates or predictors are called *features*. The dependent variable is referred to as *response* in the context of a regression model.

approaches which may results in functional form misspecification, They directly learn the relationship between variables from the data and optimally choose the parameters over a broad grid specific to the data.

I apply random forests (RF) to predict wheat price in Birr per kg and complement it with eXtreme Gradient Boost (XGB) for robustness purposes. [15] I select these models because they are more interpretable than Neural Networks, more versatile than Support Vector Machines, and repeated sampling make them more accurate (Athey and Imbens, 2019).

To estimate the ML model, I standardize the features to ensure that their scale does not influence the feature's importance. Then, I randomly split the data into training (70 %) and test samples (30 %), and use five-fold cross-validation during training. Next, I predict the wheat price for the farmers in the 30% test sample and compute the relevant statistics (e.g., out-of-sample mean squared error and R-squared).[16]

To evaluate the model's performance and interpret the features, I follow standard practice using the root mean squared error (RMSE) as the main criteria to compare models' accuracy. I also report the square of the Pearson correlation coefficient (i.e., the correlation between the actual and predicted price), similar to the R-squared in linear least squares regressions.

The main issue in ML algorithms is related to their interpretability. To overcome this issue, I present features importance measure. This corresponds to the increase in the mean squared error of prediction when I randomly exclude a given variable from the model. A high feature's importance represents an increase in the mean squared error due to that predictor's omission. However, it does not provide the sign of the association between features and the response (i.e., wheat price predicted). Hence, I compute Shapley values (SHAP) to increase the readability of XGB model.

The SHAP values correspond to the unexplained part of the model for each observation and the sign of predictors association with the response.[17] A positive (negative) SHAP value shows 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 is, the more important the corresponding feature for the model.

7 Results

In this section, I consider four different cases. First, I test whether quality measures described in Section 4 is recognized on the market by a premium price. Second, I estimate the heterogeneous effect

[15] See Hastie et al. (2009) and Chen and He (2015) for more details on random forests and eXtreme Gradient Boosting, respectively.

[16] I conduct a grid search over a range of parameter values during model training and select them to minimize the errors.

[17] See Amin et al. (2021) for more details.

of market conditions on quality attributes price premium. Third, I estimate whether alternatives marketing mechanisms are relevant to enhance quality recognition. Finally, I use machine learning methods to identify the most important predictors of price.

7.1. Quality price premium

7.1.1. Overall grade

I first present results on quality recognition using objective and subjective quality measures. Table 4 shows the presence of a price premium for high-quality wheat using either measures of quality.

Columns (1) to (4) show consistently positive and significant association 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 percent price premium for objective high-grade compared to low-grade (column 2), and an 8 percent premium for subjective high grade in column (4). Similar results are found upon 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 high-quality producing ones. Results in columns (7) and (8) report the expected price premium using the subjective quality measure. Accordingly, both high and medium-quality producing farmers expect to earn a price 5 percent higher price than lower-quality producing ones. Overall, results from Table 4 suggest that farmers are well aware of their wheat quality and that they rightly expect price premiums for higher quality outputs. These results contrast with recents ones by Bold et al. (2021) in Uganda, who assess maize quality in lab and fail to identify a quality-price premium for high-quality farmers in a randomized experiment.

Results from Table 4 also suggest minor if any differences in price premium between high and medium quality wheat. This may relate to the compounding effect of aggregate quality grades, which may hide individual effects of various attributes. I turn to 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)
Objective quality:								
High	0.07***	0.02***			0.07***	0.01**		
	(0.02)	(0.00)			(0.02)	(0.00)		
Medium	0.03*	0.01*			0.03**	0.01		
	(0.02)	(0.00)			(0.01)	(0.01)		
Subjective quality:								
High			0.12***	0.08***			0.07**	0.05***
			(0.03)	(0.01)			(0.03)	(0.01)
Medium			0.08***	0.07***			0.05*	0.05***
			(0.02)	(0.01)			(0.03)	(0.01)
Constant	3.10***	2.41***	2.83***	2.55***	3.07***	2.40***	2.90***	2.57***
	(0.22)	(0.09)	(0.21)	(0.03)	(0.22)	(0.08)	(0.23)	(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

Source: Author's computation based on 2019/2020 wheat survey.
Notes: Price and expected price are expressed in logarithmic form. High quality is considered as value of reference. Included controls: 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.

7.1.2. Quality attributes

The extent to which an attribute can be observed can play an important role in its recognition on market (Abate and Bernard, 2017, Fafchamps et al., 2008, Hoffmann and Gatobu, 2014, Jano and Hueth, 2014). Although assessing the quality of different crop attributes is possible, the testing protocol requires lab equipment. Quality testing being based on a homogeneous volume of grain sample, the per kg cost of testing decrease with the overall volum of grain to be assessed. Thus, objective quality measure is rarely performed in local markets (Abate et al., 2021). From our data, I can investigate the extent to which unobservable quality is rewarded by the market.

The relationships between market price and objectively measured attributes of quality are presented in Table 5. I reverse the impurity scale for convenience of interpretation, such that the variable now increases with wheat purity. Of the three attributes, only purity—the only one directly observable—is valued by traders (column 1). The results are somewhat smaller but remain significant upon introducing market and time fixed effects in column (4). On average, a 1 percent increase in purity is associated with a 2 percent price premium—equivalent to 1 Birr/kg. In comparison, there is no reward for unobservable quality attributes, whether moisture content our flour-extraction rate as measured by test-weight.

These results are well alilgned with that of other studies in Sub Saharan Africa. In Benin, Kadjo et al. (2016) finds a 3 percent 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 rates. In Ethiopia, Abate and Bernard (2017) use test-weight as indicator of wheat quality in Ethiopia. They find that Ethiopian wheat farmers received an average price that does not discriminate them by test-weight level.More broadly, these findings provides new evidence to the recent literature on demand-side constrained for quality-upgrading. In line with Fafchamps et al. (2008), I find that attributes measurable without costs are valued by markets. However, it is not sufficient as quality covers unobservable and observable attributes that exert weak if any correlation with one another.

Table 5: Quality attributes price premium

	(1)	(2)	(3)	(4)	(5)	(6)
Impurity	0.05***			0.02***		
	(0.01)			(0.00)		
Moisture		-0.01			0.02	
		(0.07)			(0.01)	
Test-weight			0.12			0.01
			(0.09)			(0.03)
Constant	3.04***	2.94***	2.43***	2.55***	2.45***	2.45***
	(0.18)	(0.23)	(0.38)	(0.03)	(0.06)	(0.13)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	Yes	Yes	Yes
Market FE	No	No	No	Yes	Yes	Yes
N	2725	2856	2731	2725	2856	2731

Source: Author's computation based on 2019/2020 wheat survey.
Notes: All variables are expressed in logarithmic form. Included controls: 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 conditions

Next, I examine whether price premiums vary with market conditions. I consider two market conditions in particular: the market type within the *woreda*, the level of competition on the given market day. Results are presented in Table 6, and show a significant and positive interaction between market type and the test-weight onto the wheat price obtained by farmers. Accordingly, a 1 percent increase in test-weight level is associated with an 11 percent price higher price, but only on district markets and not on secondary ones. By comparison, while I find a positive price premium for wheat purity, as before, there is not clear differences across market types. I fail to find either a linear or a heterogeneous relationship between price and moisture content.

Existing works on quality recognition on crop markets typically find 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 find that promoting the diffusion of information about unobservable attributes has a positive impact on their price premium (Abate and Bernard, 2017, Bernard et al., 2017, Magnan et al., 2021). However, these past studies assume markets' homogeneity. Our results show a difference in quality recognition for test-weight between district and secondary markets. It could either indicates that buyers' interest for test-weight is higher on district markets or that high-quality farmers self-selected into these markets. Atthis stage, these results must therefore be interpreted with caution.

Table 6: Quality attributes price premium, with heterogeneity by market role

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

Source: Author's computation based on 2019/2020 wheat survey.
Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. I reverse impurity scale: high value is now purest wheat. District market is equal to 1 if the market j is the main market in the *woreda*. The quality term in the interaction variable corresponds to the quality attribute specified at the top of the column. Included controls: 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 issue is of important relevance as traders' market power can create important constraints for investment decisions and quality upgrading (Swinnen and Vandeplas, 2015, 2010). In such case, traders have not incentives to reward quality as farmers have limited outside option. Moreover, it is possible that with more traders, it will be harder to coordinate or collude. More traders may result in a broader diversity of traders, including those who potentially have a higher valuation of higher-quality wheat. However, the existing literature on this topic is mainly on global and export-oriented supply chains (Reardon and Hopkins, 2006, Swinnen and Vandeplas, 2010). Competition in local markets is also of academic interest (Bergquist and Dinerstein, 2020, Dillon and Dambro, 2017). Given that local markets remain the principal option for farmers to sell their outputs, it is helpful to measure the extent to which market competition plays a role in quality recognition. In particular, given the low spot market outside option available to farmers, market competition helps to understand the importance of market condition in quality recognition. For instance, Abate and Bernard (2017) find that in their sample of Ethiopian wheat growersthat most usually sell and shop in their local Kebele market, and may therefore be captive to traders on this market.

Table 8 shows the heterogeneous relationship between attribute price and competition. Columns (2), (3), and (4) of Table 8 show that higher competition is negatively affected with market price, albeit to a lower extent in the most competitive markets.

However, and as discussed in Section 6, one be concerned 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: the occurrence of a religious day, whether it rains on the pre-market week and market day. Then, the interaction term, which captures the heterogeneous effect of competition on quality price premium, is also endogenous. Hence, I include an interaction term between our instruments and quality attributes as new instruments (Wooldridge, 2010). I first assess whether the instruments used are good predictors of competition. Results in Table 7 show that rainfall and occurrence of the 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 instruments are not weak. Except for Impurity in Column (6), the F-statistic exceeds 10 in other estimates, indicating that the instruments are good predictors of competition.

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

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

Source: Author's computation based on 2019/2020 wheat survey.
Notes: Competition corresponds to the number of traders per farmer in market j and is expressed in logarithmic form. Religious day is a dummy equals to 1 if the market day occurred on a religious day in market j. Pre-market week rainfall is a dummy equals to 1 if rainfall were higher than 10mm in the previous 7 days in market j. Market day rainfall is a dummy equals 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 endogeneity of competition has strong effects on the results. As reported in Table 8, I find that accounting for endogeneity of competition level increases the price premium for impurity and moisture content compared to the OLS estimates, whereas the effect for test-weight becomes insignificant. The size of the coefficient of the interaction terms triples when using IV estimates in Columns (6) and (7) compared to OLS in Columns (2) and (3).

Table 8: Quality attributes price premium, with heterogeneity by market competition

	OLS				2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quality variable:	None	Impurity	Moisture	Test-weight	None	Impurity	Moisture	Test-weight
Competition	-0.15	-0.07	-0.96**	-1.48***	-0.14	0.47	-2.86**	2.10
	(0.09)	(0.07)	(0.38)	(0.33)	(0.14)	(0.25)	(1.42)	(4.12)
Quality		0.01	-0.01	-0.02		-0.05	-0.08	0.06
		(0.00)	(0.01)	(0.02)		(0.01)	(0.05)	(0.09)
Competition $\times$ Quality		0.08***	0.31**	0.30***		0.24**	1.00*	-0.58
		(0.02)	(0.13)	(0.08)		(0.10)	(0.55)	(0.97)
Constant	2.58***	2.58***	2.57***	2.60***	2.62***	2.61***	2.70***	2.54***
	(0.02)	(0.08)	(0.10)	(0.13)	(0.03)	(0.12)	(0.20)	(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
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

Source: Author's computation based on 2019/2020 wheat survey.
Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. I reverse impurity scale: high value is now purest wheat. Competition is the hyperbolic sine transformation of the number of traders per farmer. 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. I additionally interact quality with the previous instruments.Included controls: 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.

These results demonstrate that both impurity and moisture become more price discriminant as the competition increases. The incentives to supply high-quality wheat is higher on competitive markets as traders offer higher price premiums for purer wheat. As inspecting impurities does not entail additional costs for traders, rewarding purer wheat can be a differentiation strategy for them in a competitive environment to secure the best wheat supply. Albeit moisture is unobservable to the naked eyes, field observation suggest that the most experienced traders may approximate it by chewing grain. Thus, it is costless for some traders to measure moisture, even if it is simply an imperfect estimation. Given that competition between traders increases both demand and outside 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 for it whether on higher or lower competition markets.

These results resonate with that of Bold et al. (2021), who find that entry of buyers rewarding high quality on a set of markets, increases the equilibrium price for these markets. In contrast, Bergquist and Dinerstein (2020) find that as traders have significant market power, new entrants will not modify the market environment because they will join collusive agreements with incumbents.

More broadly, these findings highlight that market conditions are key determinants of the existence of rewards for quality. However, my findings also highlight the limits of market forces when it comes to rewarding unobservable attributes of crops. Thus, alternatives to traditional market mechanisms can emerge as a second-best solution, which I discuss below.

7.3. Alternatives to market?

I have shown that the market as decentralized allocations mechanisms failed to recognize unobservable attributes by a price premium. For Fafchamps (2003), formal institutions are inefficient in SSA agricultural markets due to small transaction size. As a result, 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), certification services (Bernard et al., 2017), vertical integration (Deutschmann et al., 2020), or informal such as farmers-traders relationship based on trust and repeated interactions (Casaburi and Reed, 2019, Fafchamps and Minten, 1999).

Here, I examine this question using three variables: relationship between traders and farmers, existence of a miller plant at market site, and existence of a wheat producers cooperatives. Each variable captures a slightly different aspect of alternatives to market. First, the farmer-trader relationship emerges as a credible alternative to minimize the contract breach risk (Fafchamps, 2001). Without protection against opportunistic behavior, constructing personal trust through repeated interactions is often a reliable substitute to market allocations. Although Fafchamps and Minten (1999) find that quality provision is not central in a relationship, I am looking further by considered whether observable or unobservable attributes are valued differently. Second, value chains such as the wheat value chain in Ethiopia can be long and involve a fairly large number of intermediaries (Osborne, 2005). Multiplication of intermediaries increases final costs as each agent expects to make a profit. However, intermediaries are not final buyers of these goods, and their demand for quality only depends on that of downstream value chain actors. Millers are the main end buyers of wheat before transformation into flour. Their demand is largely driven by quality as impurity, moisture of flour-extraction rate (test-weight) significantly affect the volume and quality of flour that they can obtain from it. A Thus, I expect that presence of miller plant on local markets reduces the length of the value-chain size, and results in a higher price for higher-quality wheat.

Lastly, I investigate the relationship between price returns to quality and the presence of cooperatives on market site. From fields observation, cooperatives are often interested in the quality of the wheat that they aggregate under the cooperative's brand name. A number of them assess the quality of farmer's wheat individually, before aggregating it with others. From a farmer's perspective, selling top cooperative has drawbacks, in that payment is often done with a month delay. Farmers' time preference affects their marketing choices between market or cooperative way.

Table 9: Quality attributes price premium, with heterogeneity by alternatives to market

	(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***	0.05**	-0.01	0.01***	0.05*	-0.02	0.01	-0.03	-0.01
	(0.01)	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)	(0.03)
Relationship	0.01	0.11*	-0.19						
	(0.01)	(0.06)	(0.21)						
Relationship × Quality	-0.01	-0.04*	0.05						
	(0.01)	(0.02)	(0.05)						
Millers × Quality				0.01	-0.04	0.10**			
				(0.01)	(0.04)	(0.04)			
Cooperatives × Quality							0.02**	0.08**	0.07*
							(0.01)	(0.03)	(0.04)
Constant	2.55***	2.38***	2.51***	2.55***	2.44***	2.37***	2.46***	2.35***	2.24***
	(0.03)	(0.06)	(0.14)	(0.03)	(0.05)	(0.09)	(0.09)	(0.09)	(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

Source: Author's computation based on 2019/2020 wheat survey.
Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. I reverse impurity scale: high value is now purest wheat. Relationship is a dummy equals 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. Included controls: 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 market alternatives. I first investigate the effect of farmer-trader relationship measured by the survey question "Have you sold our wheat to your usual trader?" In theory, such informal contract farming can provide a commitment mechanism to resolve the asymmetric information problem.Yet, I do not find of these effects. If anything, I find in column (2) that if markets reward moisture content, the premium is null for those farmers with long term relationship with their buyer. This result matches those of earlier work by Fafchamps et al. (2008) in India. They find that the farmer-trader relationship is not used for ensuring quality provision and facilitating quality inspection.

The second aspect of alternative to market mechanisms is the presence of millers on site. Results are presented in Columns (4) to (6). As before, I find that the market rewards impurity and moisture content positively, although no specific rewards occur upon the presence of a miller on site. In contrast, results in Column (6) point to a positive reward to unobservable quality (test-weight) where one finds a miller plant. In these markets, a 1 percent increase in test-weight score leads to a 10 percent price premium. In Ethiopia, millers pay significant attention to flour-extraction rate. Two bundles of wheat, identical when it comes to observable attributes (e.g. impurity) may however exert large differences in flour-extraction rate, thereby affecting millers' profit Abate and Bernard (2017). The presence of miller plant on market site may affect rewards to such attributes, through both informationnal effects and reductions in the length of the value chain that otherwise contribute to dilute the incentive of procuring higher quality wheat.

Last, results in columns (7) to (9) of Table 9 point to a positive effect of the presence of cooperatives on price rewards to all quality attributes, whether observable or unobservable. On average, when there is a cooperative, a 1 percent increase in the quality score is associated with a 2 percent price premium for impurity, 8 percent for moisture, and 7 percent 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 who have access to cooperatives on the market may benefit from such agricultural technology and produce higher quality wheat. Indeed, 89 and 60 percent of Ethiopian farmers who has access to cooperatives on the market in 2014-15 purchase fertilizers and seeds respectively (Abate and Bernard, 2017). In Ethiopia, cooperatives usually provide quality assessments when they collected output. Once aggregated, cooperatives may either resell bulked wheat to millers or directly transform it into their flour factories. These results may inform the role that may play cooperatives in quality upgrading in local markets.

7.4. Geographic conditions and marketing time

7.4.1. Market location characteristics

Several studies in SSA show that geographic location of rural markets affect their equilibrium prices (Aker, 2010a, Minot et al., 2019, Vandercasteelen et al., 2018). Here I examine this question using geographical and demographic variables suggestive of the market environments. Each variable captures a slightly different dimension. The first is defined based on the market's physical distance to Addis Ababa, the main demand area. The second captures whether the market is located in one of the main wheat surplus area of Ethiopia. I use the classification established by Minot et al. (2019) to identify the surplus and deficit production zone. The last one hinges on 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 scales which may reduce transaction costs.Areas with higher population density are also more likely to be more urbanized, areas where demand for quality may be higher (Vandercasteelen et al., 2018).

Results are presented in Table 10. Together, they point to significant associations between market's geographical characteristics and price premium for unobservable quality. In column (3) I find a positive interaction between distance to Addis Ababa and reward to unobservable quality. With distance to Addis Ababa possibly correlated with differences in soil quality across market locations (and thereby unobservable quality), one must be cautious in interpreting this result as a market-integration related one. In fact, the classification of markets according to Ethiopia's main surplus areas highlights a positive return to unobservable quality in column (6). Last, column (9) exhibits a positive interaction between population density and price return to unobservable quality.

Table 10: Quality attributes price premium, with heterogeneity by location markers

	(1) Impurity	(2) Moisture	(3) Test-weight	(4) Impurity	(5) Moisture	(6) Test-weight	(7) Impurity	(8) Moisture	(9) Test-weight
Quality	0.01	0.01	-0.01	0.01	0.05***	-0.03***	0.03	0.05	-0.18
	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.07)	(0.11)
Addis Ababa × Quality	0.01**	0.03	0.11*						
	(0.01)	(0.03)	(0.06)						
Surplus Area × Quality				0.01	-0.03	0.12***			
				(0.01)	(0.02)	(0.03)			
Population Density × Quality							-0.01	-0.01	0.04*
							(0.01)	(0.01)	(0.02)
Constant	2.45***	2.37***	2.23***	2.45***	2.36***	2.13***	2.45***	2.37***	2.21***
	(0.09)	(0.10)	(0.15)	(0.09)	(0.11)	(0.14)	(0.10)	(0.14)	
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

Source: Author's computation based on 2019/2020 wheat survey.
Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. I reverse impurity scale: high value is now purest wheat. Addis Ababa is a dummy equals to 1 if the market j is among the furthest market 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. Included controls: 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-based in SSA, farmers face far risks during the agricultural season that affect their marketing behavior. Many smallholder farmers must deal with liquidity constraints at harvest time to pay back agricultural loans or to 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 such as fungi, rodents, mold, and insects. For these reasons, price premium to various quality attributes may differ across dates of survey rounds from which we obtained this data. Results are presented in Table 11. Overall, I find only limited evidence that transaction date is associated with differential rewards to quality. If anything, results in column (1) suggest that traders give a price discount for the impurest wheat supplied. However, impurity becomes not rewarded later in the commercialization season. This matches closely with earlier work by Kadjo et al. (2016) on the rural maize sector in Benin.

Table 11: Quality attributes price premium, with heterogeneity by marketing period

	(1) Impurity	(2) Moisture	(3) Test-weight	(4) Impurity	(5) Moisture	(6) Test-weight
Quality	0.02***	0.00	0.01	0.02***	-0.01	0.09
	(0.01)	(0.02)	(0.04)	(0.01)	(0.03)	(0.12)
Follow-up	0.06*	0.01	0.01			
	(0.03)	(0.09)	(0.01)			
Follow-up × Quality	-0.02*	0.03	0.01			
	(0.01)	(0.03)	(0.09)			
Survey week				0.04	0.03	0.06
				(0.03)	(0.03)	(0.06)
Survey week × Quality				-0.00	0.01	0.00
				(0.00)	(0.01)	(0.01)
Constant	2.44***	2.40***	2.37***	2.29***	2.30***	1.85***
	(0.09)	(0.10)	(0.22)	(0.14)	(0.15)	(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

Source: Author's computation based on 2019/2020 wheat survey.
Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form. I reverse impurity scale: high value is now purest wheat. Follow-up is a dummy equals to 1 if the 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.Included controls: 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.

7.5. Robustness check

I propose some robustness checks to ensure the validity of our previous estimates. Picking the right set of control variables is a complex choice that can lead to omitted variable bias when I include too few controls or the wrong ones. Conversely, selecting too many variables may leads to overfitting problem. I rely on the post-double selection (PDS) LASSO procedure presented in Belloni et al. (2013). The main advantage of PDS is to pick control variables consistently and avoid standard errors estimation issues. In practice, I first use a LASSO procedure to select the covariates statistically correlated with the independent variable (i.e., quality measures). I then do the same to select the covariates correlated with the dependent variable (i.e., price). The LASSO estimator reaches a sparse solution by setting irrelevant covariates coefficients to zero. Hence, I obtain a vector of covariates which are selected in both steps. This method improves efficiency by finding variables predictive of the outcome and reducing the residual variance. It presumes that the model is approximately sparse, meaning that in the true model estimated, only a restrained number of variables matter.

Table A.6 shows the attributes price premium independently of market conditions as above in Table 5. As in Table 5 a price premium is only paid for impurity. This suggests that when I consider markets as a homogeneous group, only observable quality attributes are recognized and valued.

Table A.7 shows the attributes price premium with heterogeneity by market type as in Table 6. I find similar results than in Table 6. This suggests that there is a heterogeneous price premium by market type. I show that test-weight is valued exclusively in the district market.

Table A.8 presents results for price premium with heterogeneity by alternatives to market mechanisms. The results are identical to those observed in Table 5. First, the farmer-trader relationship is not used to ensure quality provision and recognition. Second, when millers are present on the market, I observe a price premium for test-weight. Lastly, when a cooperative is directly available on the market, all quality attributes are rewarded.

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

Previous work has suggested various farmers-level solutions to increase local agricultural prices (Bergquist and Dinerstein, 2020, Casaburi and Reed, 2019, Karlan et al., 2014). It assumes that the main barriers to enhance price might be overcome at individual level. However, such interventions may have limited impacts if market conditions are the main price determinants. Here, I examine whether market level or farmers level characteristics are more likely to determine wheat price.

Table 12 presents the out-of-sample root mean squared error (RMSE) and square of the Pearson correlation coefficient for wheat price. I do not observe large differences in performance between random forest (RF) and eXtrem Gradient Boosting (XGB). However, XGB model looks more accurate as the confidence interval is smaller than for RF. I use all features presented above in Table 1 and 2.

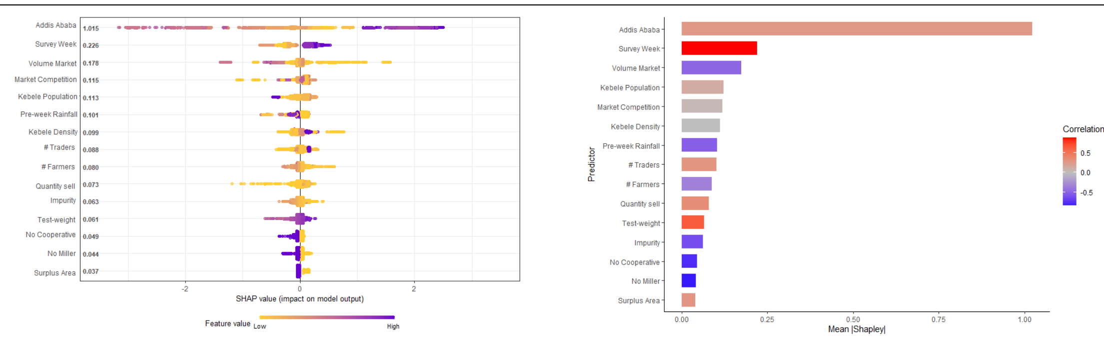
Table 12: Prediction (out-of-sample) accuracy for wheat price

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

Source: Author's computation based on 2019/2020 wheat survey.
Notes: RMSE is the out-of-sample root mean-squared error computed using the out-of-sample over 5-fold estimations. Bootstrapped 95 percent 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.

The key question is to determine which features are the most predictive and the direction of the association with the response. Figure 8a plots the Shapley values of the fifteen most predictive features using XGB. The SHAP values and the features are placed respectively on the horizontal and vertical axis. 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 combination of the predictors. For instance, the feature ”volume market” decreases the predicted values (SHAP value is negative) for most observations when included in the model. Clearer colors imply smaller values of the feature: lower values of volume traded on the market are observed where SHAP is positive. However, based only on Figure 8a it can be challenging to fully understand the direction of association between the feature and the predicted price.

Figure 8: Top predictors association with prediction of wheat price: eXtreme gradient boosting model



(a) Shapley values against the features **(b)** Top 15 predictors of wheat price

Source: Author’s computation based on 2019/2020 wheat survey.
Notes: Figure 8a 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 indicate the average contribution of the variable in prediction and is on the vertical axis. Darker color corresponds to higher values of the predictor.
Figure 8b 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 8b displays a better form to understand the association between features and predicted price. Average SHAP values are plotted by features on a bar diagram, colored by the correlations between the feature and its SHAP values. Distance to Addis Ababa, 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 cooperative and miller have a negative relationship. Moreover, the quantity sold by farmers and the test-weight values are positively related to price, while impurity has a negative association. I find that most of the best wheat price predictors are market conditions characteristics rather than farmers 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, underlining the importance of market conditions in analyses of price premiums to quality - and thereby farmers' incentive to invest in improving the quality of their output. Measuring and quantifying more accurately the potential effect of market conditions variation on quality price premium may be a fruitful avenue for future work.

8 Summary and Concluding Remarks

Food crops' quality issues are among the main concerns that SSA countries must address in the upcoming future to reach food self-sufficiency. A large number of empirical works have been using supply-side approaches to alleviate farmers' constraints in quality-upgrading such as liquidity, risk, information, technology access (De Janvry and Sadoulet, 2020). Following recent empirical papers focusing on demand-site constraints (Abate and Bernard, 2017, Bernard et al., 2017, Bold et al., 2021), I present some evidence that imperfect market recognition on quality must be address to enhance quality supply. Using original survey data collected in 60 Ethiopian wheat markets, I have examined the extent to which quality is rewarded in the Ethiopian wheat market. I find that farmers have an imperfect insight into the quality they are supplying and are imperfectly rewarded for providing high-quality wheat. While a significant price premium is paid to farmers for purer wheat (i.e., observable attribute), I find that moisture and test-weight (i.e., unobservable attributes) are not rewarded. This result is consistent with the conceptual framework developed in Fafchamps et al. (2008) and supports the idea that quality issue is a current concern for traders.

Previous studies implicitly assume that farmers sell their outputs on homogeneous markets. However market conditions are highly unequal, locally-specific, and thereby impact transaction costs which may also affect quality recognition. I present evidence on quality price premium variation across market conditions and identify various market features that are associated with the existence of price premium to observable and/or non-observable quality attributes. Ampon others, price premium for observable quality attributes increase with the level of market competition, while presence of millers and/or cooperatives on market sites affects returns to non-observable quality attributes.

These results do not rely on a purposefully designed trial, and several of the highlighted relationships must be interpreted as exploratory. Nevertheless, these results suggest that current policies proposed to release farmers' constraints (e.g., technology adoption subsidies, providing financial services and extension services development) would do little to promote quality-upgrading as long as quality is not fully rewarded at market level. Given the positive correlation between market competition and quality recognition , policymakers might be interested in promoting competition to enhance quality price premium, which may increases farmers' returns in quality-upgrading.

However, implementation of these policies in a weakly institutionalized and imperfect market context may worsen market functioning 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). Hence, policy intervention must be evaluated on a case-by-case basis to address markets issues experienced by local actors. For instance, policies have been promoting alternatives marketing channels such as vertical coordination and cooperatives, to enhance quality in local markets. Nevertheless, they represent only a small share in local marketing channel. Other studies propose to encourage quality-upgrading through the promotion of third-party certification available to small-scale farmers to reveal unobservable attributes at low costs (Abate et al., 2021). From farmers' side, recent evidence do point to a significant demand for such services (Anissa et al., 2021). The extent to which traders are willing to rely on such services remains however largely unknown.

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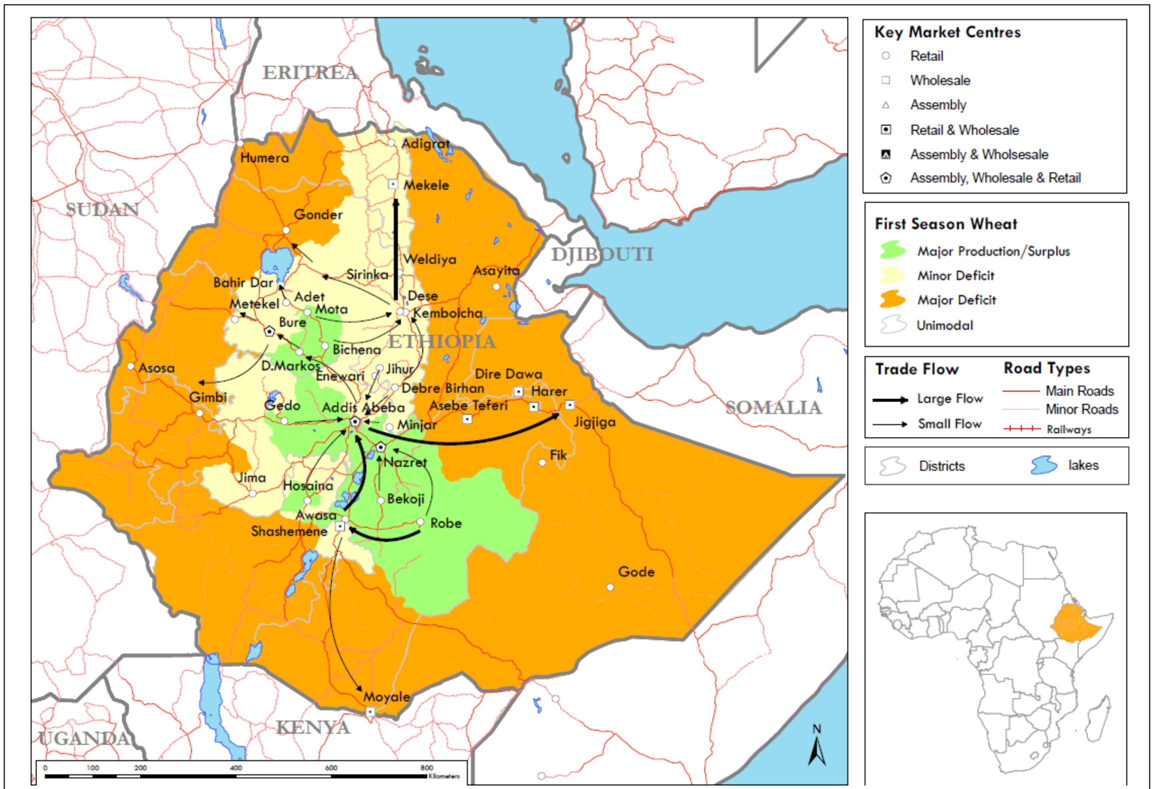
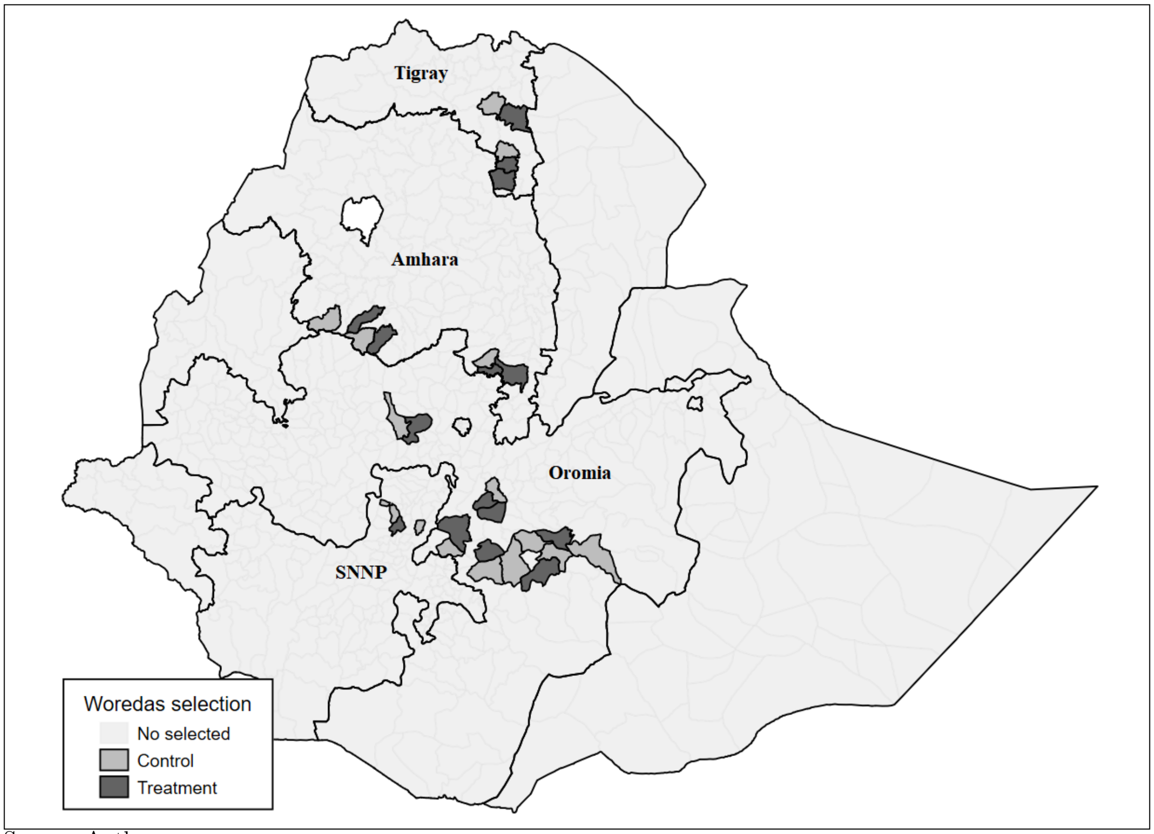
A Appendix

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



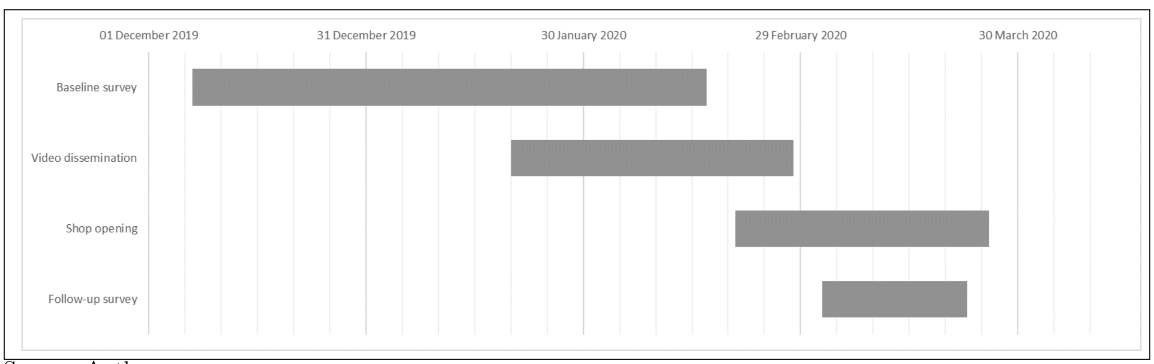
Source: FEWSNET (in FAO, 2014).

Figure A.2: Study zone and initial RCT allocation



Source: Author.

Figure A.3: Timeline

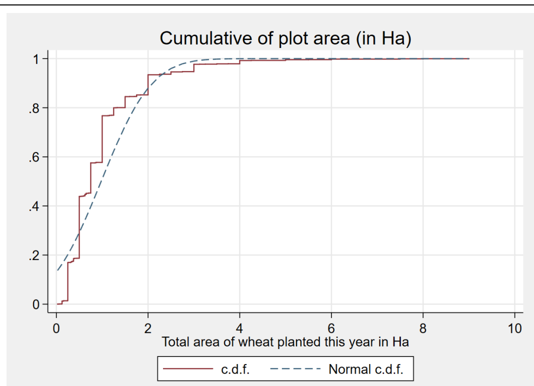


Source: Author.

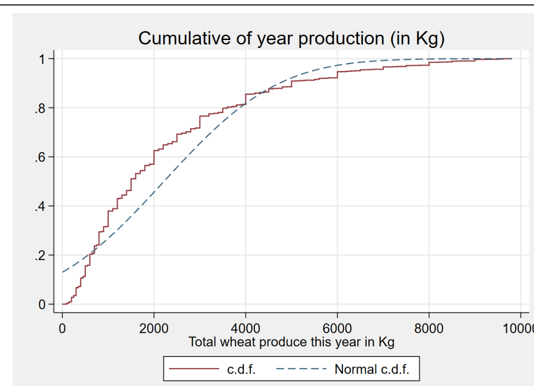
Figure A.4: Example of Facebook population map

Source: Google maps.
Note: Red squares indicate houses detected.

Figure A.5: Cumulative distribution of plot area and year production



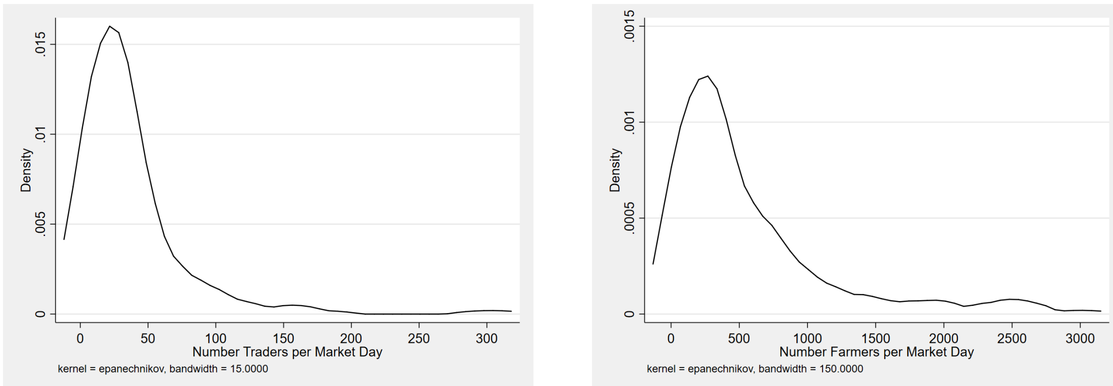
(a) Cumulative distribution of plot area (in Ha)



(b) Cumulative distribution of year production (in Kg)

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

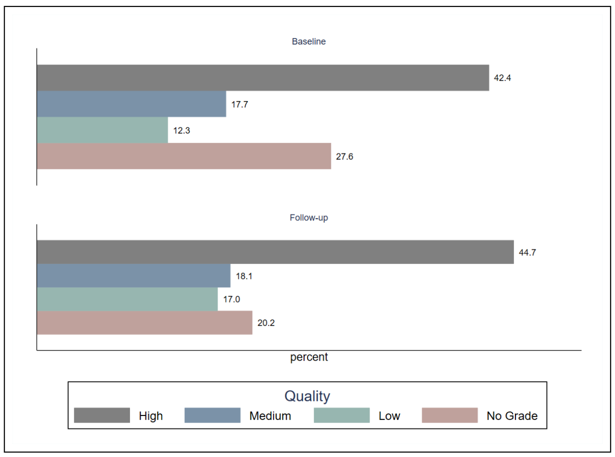
Figure A.6: Number of traders and farmers on market day



(a) Number of traders **(b)** Number of farmers

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]

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 impurity content of 6% is considered as high-quality in this dimension.

Table A.2: Balance test of market structure between survey rounds

	Obs.	Mean Baseline	Mean Follow-up	Diff.: p value
Competition	3484	0.10	0.17	0.00***
Estimated number of farmers	3484	681.98	447.74	0.00***
Estimated number of traders	3484	30.55	50.33	0.00***

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

Table A.3: Balance test of market structure between the market type

	Obs.	Mean Secondary Market	Mean Main Market	Diff.: p value
Competition	3484	0.14	0.13	0.59
Estimated number of farmers	3484	353.90	778.14	0.00***
Estimated number of traders	3484	26.87	53.20	0.00***

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

Table A.4: Balance test of market structure between normal and religious market day

	Obs.	Mean Normal Day	Mean Religious Day	Diff.: p value
Competition	3484	0.13	0.15	0.04**
Estimated number of farmers	3484	590.15	295.69	0.00***
Estimated number of traders	3484	40.63	34.42	0.09*

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

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

	Price prediction			
	Accurate estimation	Under estimation	Over estimation	Total
Objective quality				
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
Subjective quality				
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

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

Table A.6: Price elasticity of quality attributes: covariates selection using a post double LASSO procedure

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

Source: Author's computation based on 2019/2020 wheat survey.
Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form.I reverse impurity scale: high value is now purest wheat. Relationship is a dummy equals 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 on 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.7: Price elasticity of the 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***	0.04	-0.01
	(0.01)	(0.03)	(0.02)
District Market × Quality	0.01	-0.03	0.10*
	(0.01)	(0.03)	(0.05)
Constant	2.50***	2.60***	2.23***
	(0.02)	(0.05)	(0.20)
Control	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Market FE	Yes	Yes	Yes
N	2683	2814	2689

Source: Author's computation based on 2019/2020 wheat survey.
Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form.I reverse impurity scale: high value is now purest wheat. Relationship is a dummy equals 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 on 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: Price elasticity of the 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:	Imp	Moist	T-w	Imp	Moist	T-w	Imp	Moist	T-w
Quality	0.02***	0.05**	-0.00	0.01***	0.05*	-0.002	0.01	-0.02	-0.01
	(0.01)	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)
Relationship	-0.01	0.11*	-0.21						
	(0.01)	(0.05)	(0.21)						
Relationship × Quality	-0.01	-0.04*	0.05						
	(0.01)	(0.02)	(0.05)						
Millers × Quality				0.00	-0.04	0.10**			
				(0.01)	(0.04)	(0.04)			
Cooperatives × Quality							0.02***	0.08**	0.08**
							(0.01)	(0.04)	(0.04)
Constant	2.58***	2.45***	2.56***	2.64***	2.49***	2.69***	2.48***	2.47***	2.49***
	(0.03)	(0.06)	(0.14)	(0.03)	(0.06)	(0.10)	(0.02)	(0.04)	(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

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

Notes: Price, impurity, moisture and test-weight are expressed in logarithmic form.I reverse impurity scale: high value is now purest wheat. Relationship is a dummy equals 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 on 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.

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

	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 _______________________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

1

Figure B.2: Growers midline survey

2020 WHEAT GROWER MIDLINE AND ENDLINE MARKET SURVEY

University of California Berkeley

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.

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Figure B.3: Market day survey

2020 WHEAT GROWER MIDLINE MARKET SURVEY

University of California Berkeley

MARKET LEVEL SURVEY

	Name	*Code*
Region		
Zone		
Woreda		
Kebele		
Market		

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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