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

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Abstract

In many Sub-Saharan countries, farmers cannot meet the growing urban demand for higher quality products. While the literature has focused on production-side constraints to enhancing smallholder farmers' output quality, there is scarce evidence of market-side constraints. Using a sample of 60 wheat markets in Ethiopia, I assess whether farmers received a price premium for supplying higher quality outputs. I exploit a unique feature of the data which precisely measures observable and unobservable quality attributes, and relate them to transaction prices. I find that observable attributes cannot serve as proxies for unobservable ones. Transaction prices further reflect this, indicating that, markets only reward quality attributes observable at no cost. However, these results hide cross-market heterogeneity. Observable quality attributes are better rewarded in larger and more competitive markets, while unobservable attributes are rewarded in the presence of grain millers and/or farmer cooperatives. Both regression and machine learning approaches support these findings.

Keywords:

JEL Codes:

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1. Introduction

In many Sub-Saharan countries, national production of staple crops fails to meet the needs of local demand (OECD-FAO, 2016). In particular, local smallholder farmers cannot often supply higher quality products that are increasingly demanded by a growing urban population, causing further dependency on imports and gradual exclusion of smallholder farmers from these value chains. Improving smallholder farmers' output quality can be hampered by production-side constraints, through various combinations of market imperfections (e.g., credit, risk, or labor), weak extension systems, and attitudinal factors, as supported by a large literature (e.g., Benyishay and Mobarak 2019; Bold et al. 2017; Carter et al. 2013; Duflo et al. 2011; Kadjo et al. 2016; Karlan et al. 2014; Magnan et al. 2021; Suri 2011). Fewer studies have investigated the issue from the perspective of output markets: the extent to which producers' uptake of quality-improving technologies depends on their expected market returns from it (Bernard et al., 2017; Bold et al., 2022; Hoffmann and Moser, 2017; Hoffmann et al., 2013; Kadjo et al., 2016; Suri, 2011).

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

This paper provides some of the first empirical evidence of the relationship between both observable and unobservable quality attributes and related market price in rural markets. It is crucial to assess the relationship in this context, where quality certification bodies are mostly unavailable to smallholder farmers (Abate et al., 2021). The study relies on a unique set of data covering 3485 farmers in 60 rural wheat markets in Ethiopia, collected during the 2019-2020 marketing season. Before the transaction, each farmer gave a subjective measure of the overall quality level (i.e., high, medium, and low grade) of their wheat, alongside the price obtained after the transaction was completed. Enumerators also collected a 1kg sample from each farmer and used appropriate equipment to establish independent and precise measures of observable (i.e., purity content) and unobservable (i.e., flour-extraction rate and moisture content) quality attributes.[1] I use these measures to compute both an overall objective quality classification (i.e., high, medium, and low grade) and to measure each quality attribute independently. While farmers can easily improve purity content through sorting of their grain before visiting the market, agricultural practices (e.g., seed selection, use of fertilizers and pesticides, harvest technologies, storage conditions) are the main determinants of unobservable attributes.

Following Abate et al. (2021) I use a principal-agent framework to model the farmer-trader relationship and study the conditions under which traders are willing to reward quality with a price premium. The model predicts that farmers will receive a price premium only for an observable attribute. However, when observable and unobservable attributes are strongly correlated, farmers can use the former to signal the supply of high-quality level of unobservable attributes. The data shows a clear positive relationship between the price obtained and overall quality classification (inclusive of all quality attributes). The results hold whether overall objective or subjective quality measures were used, suggesting that buyers recognize wheat quality in markets. In the preferred specification, a 2% to 8% price premium is observed for higher overall wheat quality. Turning to each quality attributes separately, I find no evidence of correlation between them, suggesting that farmers and traders cannot use observable attributes as a reliable proxy of unobservable ones. Further, while there is a clear positive relationship between price and observable quality measures (1% purer wheat gets a 14% higher price), there is no relationship with unobservable attributes (i.e., moisture and flour-extraction rate) despite significant heterogeneity across farmers and the crucial importance of these factors to millers downstream the value chain.

Anecdotal evidence suggests that traders receive a price premium for supplying high-quality levels of unobservable attributes to processors and millers. I therefore hypothesize that traders would incur additional screening costs to assess unobservable attributes. These costs include fixed (sunk) costs (e.g., trucks, wages) and variable costs.

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

Hence, I extended my model to account for varying market conditions that favor or inhibit quality recognition (e.g., Bergquist and Dinerstein 2020; Casaburi et al. 2013; Casaburi and Reed 2022). In particular, empirical evidence suggests that agricultural markets in Sub-Saharan Africa remain poorly integrated (Moser et al., 2009), face high transaction costs (Aker, 2010; Casaburi et al., 2013), experience unequal levels of competition (Bergquist and Dinerstein, 2020; Macchiavello and Morjaria, 2021) and limited access to infrastructure (De Janvry and Sadoulet, 2020). This extension implies that favorable market conditions such as market size, competition level, market infrastructure, and institutional arrangements lower the cost of measuring quality attributes for the buyer (trader), thereby increasing the price premium for unobservable quality.

I test these predictions together with two market-level conditions: market-based conditions that include type of market (i.e., central district market versus secondary market) and market day competition (i.e., number of traders per farmer), and alternatives to standard market transactions with market infrastructure (i.e., presence of cooperatives and milling plants) and institutional arrangements (i.e., informal trader-farmer relationship). The results show a positive price premium on observable quality in central district markets. While more competition is associated with a higher premium for attributes that can be easily (i.e., purity) and approximately (i.e., moisture) be measured, the relationship disappears for the (non-observable) flour extraction rate in a two-stage least square estimate where the daily competition level is partly determined by market-day and weekly variations in rainfall (Asfaw et al., 2010), and religious days (Prunier, 2015). Concerning market infrastructure, the presence of a nearby milling plant is positively related to price premiums for the flour extraction rate–the attribute millers value the most. In contrast, the presence of a nearby cooperative is associated with higher prices for both observable and unobservable attributes. These findings derived from conventional econometric methods are largely confirmed using a machine learning approach that tests which market conditions and farmer characteristics best predict the price obtained. At market-level, this data-driven approach identifies market competition, presence of cooperatives, and milling plants as key characteristics explaining overall price differences. At the same time, grain purity remains the strongest farmer-level predictor of price differences within a market.

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

Second, my study contributes to an emerging body of literature on the role of local market conditions in transactions. Limited access to information, insufficient infrastructure, and local institutional arrangements restrict farmers' ability to exploit market opportunities (Aker, 2010; Bergquist and Dinerstein, 2020; Casaburi and Reed, 2022; Deutschmann et al., 2020). Low market competition, particularly a lack of outside options for farmers to sell their produce, can reduce market price and returns for quality. Previous work on quality recognition has failed to take market conditions into consideration (Fafchamps et al., 2008; Kadjo et al., 2016; Magnan et al., 2021). The present paper adds to the literature by studying the interaction between market conditions and price premium for unobservable and observable attributes. In particular, I find that price premium vary across competition levels for observable attributes only at no or small cost.

Third, I provide evidence of the demand-side constraints to agricultural quality upgrading. Public policies tend to concentrate on alleviating supply-side constraints to quality enhancement, through access to extension services, credit, inputs, and risk management devices (Carter et al., 2013; Duflo et al., 2011; Harou et al., 2022; Magnan et al., 2021). However, without explicit recognition of quality in local markets, such policies may fail to generate the kind of sustainable shift toward improving the supply of high-quality crops (Bernard et al., 2017; Bold et al., 2022; De Janvry and Sadoulet, 2020). Recent studies have adopted a demand-side approach and assume that improving local traders' capacity to recognize quality will encourage farmers' supply of higher-quality products (Abate and Bernard, 2017; Bernard et al., 2017; Bold et al., 2022; Deutschmann et al., 2020; Magnan et al., 2021). In a recent randomized controlled study in the Senegalese onion value chain, Bernard et al. (2017) highlight the importance of farmers' expectations regarding market conditions on investments in quality-enhancing inputs. More precisely, they show that while supply-side constraints are unlikely to explain low-quality supply, it can be explained by uncertainty about market rewards for high quality onions. They provide evidence that farmers' awareness of changes in local market conditions results in significant and rapid responses by farmers, leading to the production of higher quality crops. The findings from the present study add to this literature by further describing the role of market conditions in quality returns, distinguishing between observable and unobservable quality attributes.

The remainder of the paper is organized as follows. Section 2 provides additional background information on the Ethiopian wheat market. The conceptual framework is outlined in Section 3. Section 4 presents the research design and the data used. Section 5 describes the main characteristics of the markets and farmers, and provides an overview of the key variables used in the analysis. Section 6 presents the empirical strategy, followed by the results in Section 7. Section 8 concludes.

2. Ethiopian wheat market

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

High transaction costs and low quality of smallholders' output are key factors inhibiting development of the Ethiopian wheat value chain (Gebreselassie et al., 2017). Smallholder farmers have limited access to modern inputs such as fertilizer and improved seeds due to incomplete credit markets, an ineffective agricultural extension service, and

[2] In this study, we refer to smallholders as those farm households cultivating less than 2 hectares.

climate shocks (Dercon and Christiaensen, 2011). Less than 1% of the wheat area is irrigated, making it vulnerable to drought (Seyoum Taffesse et al., 2012).[3] Inadequate infrastructure (e.g., few road networks, poor market information, restricted access to internet and phone networks) increases transaction costs and price volatility and reduces market integration, further contributing to limited market participation of these farmers (Minot et al., 2019). More recently, Ethiopia's agricultural strategy, led by the Federal Government of Ethiopia, has focused on transitioning towards smallholder farmers' inclusion and value chain development (Dercon et al., 2019; Tadesse et al., 2018). A key objective is to promote high-quality wheat production in order to achieve self-sufficiency.

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

Formal grading systems and standards exist for many crops in Ethiopia, particularly wheat. Quality assessment and certification, however, are limited to large (often imported) consignments and are of limited use to smallholder farmers given their small transaction sizes (typically 200kg) and the comparatively large fixed costs of quality assessment (Abate and Bernard, 2017; Abate et al., 2021; Anissa et al., 2021). Hence, spot market bargaining is based on weight and observable attributes (i.e., color, kernel size, presence of foreign matter, varietal mix).Abate and Bernard (2017) note that traders' bargaining is not based on unobservable quality attributes (i.e., flour-extraction rate). As a result, farmers can only increase their income by supplying larger volumes and investing in increase observable quality. Traders aggregate and mix individual farmers' produce and sell the aggregate output to downstream actors (e.g., millers, pasta factories, larger traders).

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

[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 led to the abolition of these quota systems.

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

3. Conceptual framework

Agricultural value chains in developing countries involve many intermediaries (e.g., middlemen, brokers) to convoy products from smallholder farmers to final consumers. At each stage of the value chain, actors typically incur costs to assess and preserve the initial quality level. While final downstream actors (e.g., processing industries, millers, supermarkets) value quality through a price premium, this premium failed to reach farmers. Thus the latter do not have incentives to invest in the type of technologies and practices necessary to supply high-quality products. Crop markets in SSA illustrate asymmetric information issues: farmers have more information on the quality of the good supplied than buyers. Since the seminal work of Akerlof (1970), the literature has investigated the role of asymmetric information on quality supply in various contexts such as insurance or job markets, and more recently on agricultural value-chain in low-income countries. In Appendix A, I present a model partially based on Mitchell (2021) and Abate et al. (2021) focusing on the farmer-trader interaction on the local spot market (the first stage of the agricultural value chain) examining the options under which a price premium can be paid for quality attributes with different degrees of observability.

Consider a farmer producing a unit of a crop each season that she will sell to a trader on local market. The trader values attribute that can be directly observable or unobservable to the naked eye. Knowing that, the farmer can supply crop with a low or high quality levels for each attribute. Producing high-quality crop is costly for farmers, incurring the cost leads to high-quality attribute with certainty. For a given attribute freely observable for farmers and traders, they have the same knowledge about its quality level. Trader rewards high-quality attribute through a price premium. Hence, a farmer would incur this cost if the cost to produce higher quality is lower than the price premium she can obtain from it.

Some quality attributes are however only observable at a cost. Either farmers (i.e., signaling) or traders (i.e., screening) can support these costs. Even though farmer does not know observe the unobservable quality in her crop, she has privately held information about her own characteristics and costs incurred whereas the trader does not. What the trader knows with certainty is the quality level of observable attribute. If there is any credible correlation between observable and unobservable attributes, quality-level in observable attribute can be used as a proxy of quality-level in unobservable one.

Therefore, the farmer can provide a high-quality level of the observable attribute as a signal for the effort made to supply crop with a high-quality level of the unobservable one. Providing this signal comes at a cost for the farmer because she has to exert an additional effort to provide a high-quality level for both the unobservable and observable attributes. This implies that when market actors can use the observable attribute as a reliable proxy of an unobservable one, the price premium should be higher than the additional effort required. Symmetrically, there is no price premium when both attributes are uncorrelated: the observable attribute cannot be used as a proxy for the unobservable one.

Traders face competitive markets and sell aggregated crops to a processor (e.g., miller) who can observe quality attributes levels regardless their observability. While, the trader receives a certain price equals to the quality of the observable attribute, she relies on farmer's quality signal for the unobservable ones. In addition, trader pays sunk costs to participate in the market and non-linear variable transaction costs varying with market conditions. Market conditions are any market characteristic that affects transaction costs such as competition, remoteness, and better infrastructure. Cost to measure quality decreases as market condition improves and increases as market condition worsen. Therefore, the price premium for a given attribute is negatively correlated with market conditions: higher price premium on markets with better market conditions. Note that premium can be null when inspecting costs are prohibitive.

This simplified model yields three testable predictions for the subsequent empirical analyses:

1. Farmers receive a price premium for supplying a crop with a high-quality level of an observable attribute.
2. Farmers do not receive a price premium for supplying a high-quality level of an unobservable attribute unless the latter is highly correlated with that of an observable attribute.
3. Traders' screening costs are lower under better market conditions. Therefore, the price premium for a given attribute will be higher on the market with better conditions. However, when cost to measure a given attribute is high enough, the associated price premium is null.

4. Research Design and data sources

4.1. Sample selection and survey

The study was conducted in open-air markets, where smallholder farmers sell their produce mainly to traders. These markets are usually held on a predetermined day of the week throughout the wheat marketing season (Figure B.2A). When they are held on more than one day per week, there is typically a primary market day and a secondary market day. The marketing season starts between October and January according to local agro-ecological conditions, and ends with the long rainy season in June or July. Based on the market sample, Figure B.2B presents the distribution of the season's length per market (i.e., marketing season), the period during which the market is open regularly. The lion share of spot-market wheat transactions happens at that moment, even though it is still possible to sell small quantity (few kilograms) out of this period essentially on retail markets. On average, markets are open 18 weeks, while the shortest are open for 12 weeks few are open all year round. Markets are spread over different agro-ecological conditions with its unique topographic-climate combination which determines wheat production suitability yielding to season length variation.

The paper uses data collected as part of a broader project conducted in Ethiopia's main wheat-producing areas: Amhara, Oromia, Southern Nations Nationalities and Peoples' Region (SNNPR), and Tigray (Figure B.3).[6] In the 2018-2019 marketing season, a census of all wheat markets in the regions was conducted to collect market-level information such as the estimated number of buyers and sellers, the volume traded, season length, and market facilities. From this census, the main wheat market and a secondary market were selected within each *woreda* (i.e., district). The main wheat market corresponds to the principal market in the *woreda* in terms of volume traded and number of participants. The secondary market was selected within 30km of the district market. It operates during the same months of the year, but usually on a different day of the week.

In each market, and for two survey rounds, enumerators collected information from 30 selected wheat farmers who came to sell wheat on the day of the survey. Before the

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

market day, two enumerators identified the two main market access roads. Then, these two enumerators were posted at the two main market access roads and they randomly surveyed one wheat farmer every 5 to 10 minutes from among those entering the market, which represents surveying one over five farmers on average. This procedure allows the construction of a representative sample of the farmers commercializing wheat on that day. The first round of the survey was conducted in December 2019 and January 2020 and the second round in March 2020, early in the wheat marketing season and at peak supply time, respectively (Figure B.4). The final sample includes 3584 farmers, 1790 for the first survey round and 1694 for the second.[7]

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

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

4.2. Quality measures

The survey collected two aggregate quality measures: (i) subjective and (ii) objective. *Subjective* quality is based on farmers' perception of the quality of their product and is mainly based on visual inspection and experience. Subjective measures are usually

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

[8]All farmers answered both interview parts, even if 1% did not sell their wheat. This high re-interview rate is unsurprising for at least two reasons. First, as the enumerators were posted at the main market entrance, the likelihood that a farmer used the same entrance twice is high. Second, farmers were paid for answering the second set of questions.

considered inaccurate, while *objective* rely on formal grades and standards established by national or international authorities, assessed with appropriate equipment that is generally unavailable in local markets (Abate et al., 2021). Previous studies have relied on either objective (Deutschmann et al., 2020; Hoffmann and Gatobu, 2014; Kadjo et al., 2016; Magnan et al., 2021) or subjective (Fafchamps et al., 2008) measures of observable and unobservable quality attributes. I combine both approaches. First, the subjective measure is obtained from farmers' self-assessment of the quality of their wheat supply on that particular day. Farmers were asked to classify their wheat on a three-grade scale (i.e., low, medium, high). Second, three quality attributes were objectively measured using the 1 kg wheat sample purchased from the farmers:

1. **Moisture rate** assesses the water content in wheat kernels. This affects seed quality and storage life. Weather conditions during the growing season and storage conditions after harvest affect moisture content. High moisture content decreases the grain's protein content, while low moisture content results in a hard grain with low flour yield.
2. **Test-weight** measures grain density and gives the potential flour yield. It is the most important attribute for the majority of millers producing flour for bakeries.[9] Soil characteristics, weather conditions, agricultural practices and technology adoption affect test-weight. Increasing test-weight is costly for farmers. For instance, they need to apply nitrogen when it is deficient and do it at the good timing which involves to assess soil quality, use the adequate variety which is often unavailable . Accurate measures are based on the weight of a standard volume of wheat, converted into kilograms per hectoliter – so-called test-weight. High test-weight indicates that the grain is well filled, resulting in higher flour yield.
3. **Purity rate** is the share of wheat free of foreign matter such as stone or other cereals in the sample. High purity means that the grain sample is free of foreign elements. A grain sieve is used to separate foreign matter from a 100g wheat sample. The residues are then weighed to give the rate of purity in the sample.

Enumerators brought wheat samples to the nearest quality-testing booth implemented as part of the broader project mentioned in section 4.1. Well-trained entrepreneurs with

[9] Pasta industries are more concerned with protein content and generally seek to purchase durum wheat as opposed to white (or "bread) wheat. Farmers supplying on the markets of the current study essentially produce bread wheat.

access to adequate equipment (e.g., hectoliter weight, grain moisture tester, sewing machine, diaphanoscope) were running the testing facility and tested each sample. On average, testing a 1kg wheat sample takes 15 minutes and costs 0.4 US dollar to cover shop variable costs or 4.5 US dollar to cover fixed and variable costs, which represent 1 kg and 13 kg of wheat valued at the market price. Each of these dimensions was graded on a three-point scale based on the government's official grading system. An aggregate grade (i.e., low, medium, high) was then computed using the lowest factor approach.[10] This resulted in a minimum quality process, adopted for simplicity, and usable in a real market context.

It is costly and time-consuming for farmers to improve moisture content and test-weight, requiring investment in agricultural practices and technologies at planting and harvesting time. However, farmers can use traditional drying, sorting, and cleaning methods to increase purity levels before going to the market. It is important to note that moisture and extraction rates are defined as unobservable attributes as they are not readily observable to the naked eye. While the lack of access to the required tools impend traders to measure extraction rate (Anissa et al., 2021), some experienced traders chew grains to have a rough idea about moisture content. Purity is fully observable and traders assess it easily at the transaction time by looking in the wheat bag. Although, sieve and scale are the necessary tools to obtain accurate tests, traders rely on visual inspection to assess purity (as informal interviews with traders confirm).

4.3. Additional Data Sources

4.3.1. Precipitation Data

I combine this data with daily rainfall estimates obtained from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) to identify the causal effects of market competition on market price (see section **??** for more details). Sparse or non-existent ground weather stations in low-income countries have led to increased adoption of satellite rainfall estimates. CHIRPS is a daily precipitation data set developed by the Climate Hazards Group (Funk et al., 2015), which provides information at a 0.5 arc-degree resolution. Dinku et al. (2018) demonstrate that CHIRPS estimates are the

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

most accurate data in Ethiopia (and East Africa), despite lower accuracy in mountainous or coastal areas.

I use market-level precipitation data for the study period (December 2019 to March 2020), to construct instrument variables capturing (i) whether the market day when data was collected was a rainy day and (ii) whether heavy rain (i.e., higher than 10 mm) were recorded in the seven days before the survey date.

4.3.2. Population density data

I relate my market price data to population density using remotely sensed data at *kebele* level. [11] I rely on buildings recorded in Facebook's Data for Good program (Facebook, 2021) to construct population density measure at the *kebele* level. Since each market is localized in a distinct *kebele*, a specific population density measure it provided for each market.

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

5. Descriptive evidence

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

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

5.1. Open air rural wheat markets

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

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

On average, 40 traders and 560 farmers from nearby localities gather on a given market day. I use the ratio of the number of traders per farmer as the main indicator of competition, similar to Krishna and Sheveleva (2017).[12] On average, there are 13 traders per 100 farmers on any given market day, albeit with significant heterogeneity. Figure 1A presents the distribution of competition per market-day, distinguishing between main and secondary markets. The distribution is skewed to the right with a lower number of traders per farmer. 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 2). This is confirmed by the formal tests presented in Table C.3.

5.2. Smallholder farmers

The sample comprises mostly small-scale wheat producers (Table 2) with an average of 0.98 Ha of cultivated wheat and an average production of 2.7 tons. These figures are similar to those observed by Minot et al. (2019) in their detailed analysis of the Ethiopian wheat supply chain. Yields per hectare are low compared to the most productive countries at both continental and global levels.[13] Smallholder farmers are mainly located in

[12] To facilitate interpretation, the variable was multiplied by 100 to re-scale.

[13] Ethiopia's average yields is equal to 2.9 tons per hectare in 2020, 2.2 and 2.5 times lower than the two continental leaders Egypt and Zambia, respectively, and almost 3 times lower than global leaders such as Belgium and Netherlands (FAO, 2020).

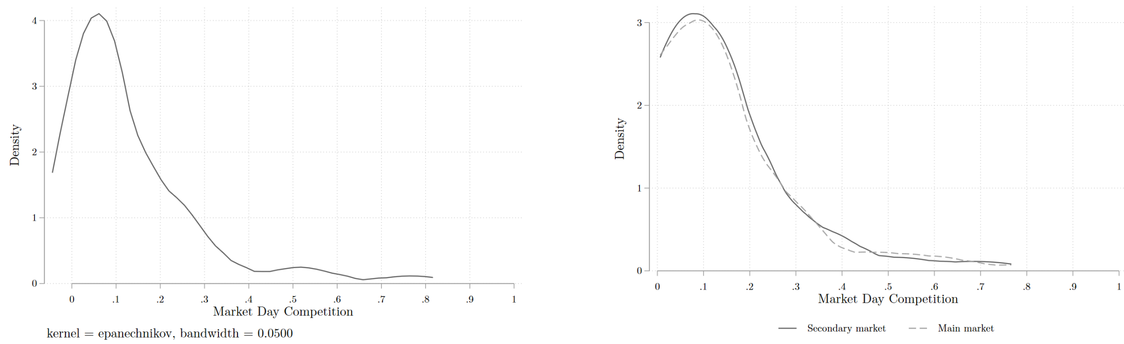
Table 1. Market characteristics

	Mean	SD	N
Panel A: 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
Panel B: 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

Source: Author's computation based on 2019/2020 wheat markets survey.
Notes. The table reports time-invariant market characteristics in panel A: market opening length in weeks, the number of villages supplying wheat to a market, the presence of a price information board at the market, milling plant or cooperative nearby, the distance to Addis Ababa and to the district capital in kms, the *kebele* population and density (people per square km). Panel B reports information gathered on market-day when surveys were recorded: whether it was a religious day, a rainy day, intense rainfall occurred the week before, the estimated number of traders this day, the estimated number of farmers this day, and the estimated number of traders per farmer this day.

isolated areas and take about one hour to reach the marketplace. Transactions are small: half of the farmers supply less than 50kg of wheat per transaction, corresponding to one standardized bag. Last, with no formal contracts related to a lack of formal institutions, over half the farmers are involved in relational contracts with traders. Typically, these contracts involve credit provisions and pre-agreed prices. Relational contracts can have several purposes, such as minimizing the risk of contract breach when formal contract enforcement is lacking (Fafchamps, 2001), ensuring access to inputs (Ghani and Reed, 2022), or quality supply (Anissa et al., 2022).

Figure 1. Market Day Competition in all markets and by market type

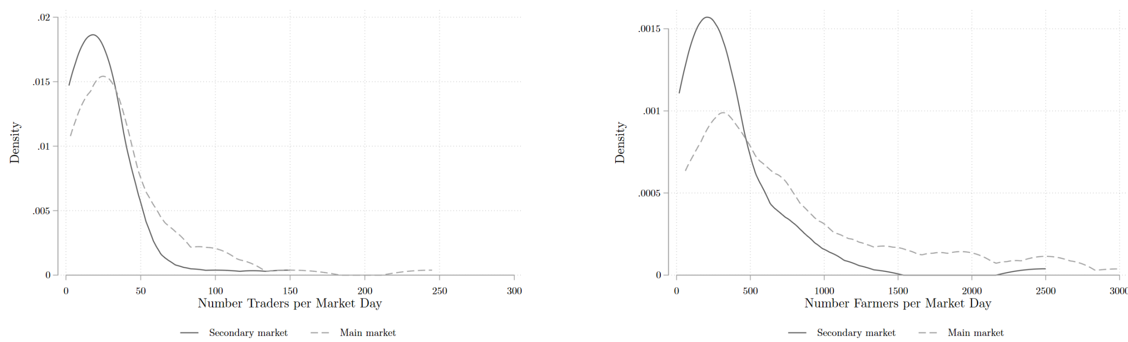


A. Market Day Competition in all markets

B. Market Day Competition by market type

Source: Author's computation based on 2019/2020 wheat markets survey.
Notes. This figure shows market day competition distribution. Market day competition is the ratio of the number of traders per farmer. Panel A. displays market day competition in all markets. Panel B. shows market day competition in main (district) markets in dashed line and in secondary markets in plain line.

Figure 2. 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.
Notes. This figure shows the distribution of the number of market actors on market day. Dashed lines represent distribution on secondary markets. Plain lines represent distribution on main (district) markets. Panel A. displays the number of wheat traders across market types. Panel B. shows the number of wheat farmers across market types.

5.3. Quality supply

As explained above in Section 4, enumerators collected samples from farmers on market days and tested them for flour extraction rate (test-weight), moisture content, and purity content to obtain objective quality measures. Based on the overall grade, Figure 3 shows

Table 2. Farmers characteristics

	Mean	SD	N
Farmer characteristics			
Age	36.37	13.58	3,484
Female (0/1)	.46	.49	3,484
Travel time (min)	58.01	46.14	3,483
Agricultural 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
Transaction price in birr/kg	13.73	2.21	3,444
Objective quality			
Purity (%)	93.40	4.75	2,758
Moisture (%)	12.67	2.37	2,895
Test-weight (%)	75.33	6.29	2,764

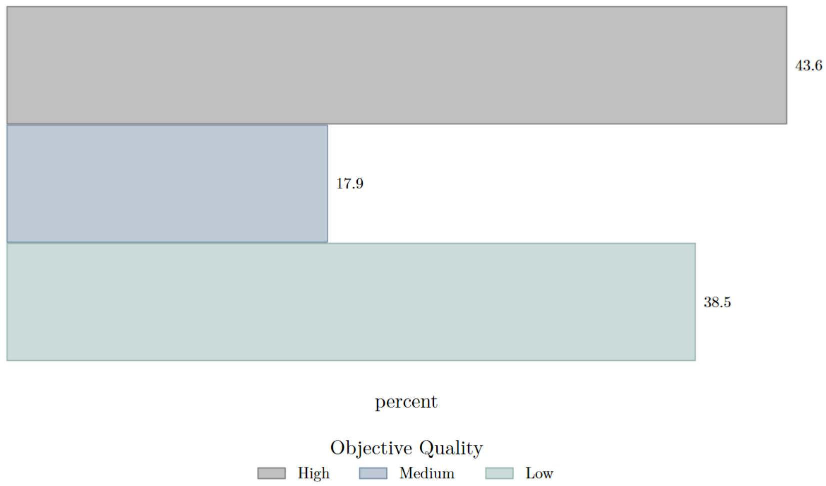
Source: Author's computations based on 2019/2020 wheat growers' survey. *Notes.* The table reports farmers characteristics: farmer age, gender, travel time to the market in min, wheat area cultivated this season in hectares, total wheat production this season in kgs, the quantity sold on survey day in kgs, whether she has a durable relationship with a trader, if she sold to her usual trader that day, the price per kg obtained from selling wheat that day, the purity content in percent, the moisture content in percent, and the extraction rate in percent.

that 43% of the wheat sample is of high quality, while almost 40% is of low quality at most (with low quality and no-grade grouped together). Quality distribution is consistent across the two survey periods (peak supply time and end of marketing season) (Figure B.7), indicative of no quality-related time-arbitrage (Kadjo et al., 2016).

Turning to each quality attribute separately, Figure 4 displays their distributions in the sample. As discussed in Section 4, test-weight and moisture are unobservable attributes, while purity content is observable.[14] While less than 1% of the wheat is not graded (i.e., below the lowest quality standard) for purity, the proportion of non-graded wheat reach almost 20% for test-weight and moisture. These differences may reflect the costs associated with producing higher quality for these attributes. While increasing purity

[14]See Table C.1 for quality attribute thresholds.

Figure 3. Objective quality distribution



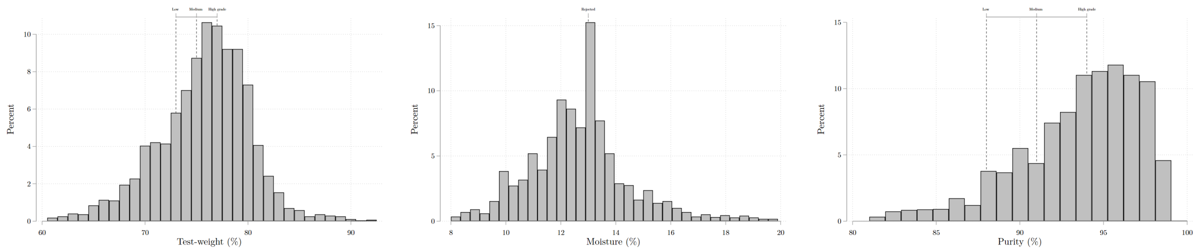
Source: Author's computations based on 2019/2020 wheat growers' survey.
Notes. The figure shows the distribution of wheat samples across quality grades based on objective assessment (i.e., laboratory test). The classification relies on three criteria: flour extraction rate (test-weight), moisture content, and purity content to obtain objective quality measure for each. Each of these dimensions was graded on a three-point scale based on the government's official grading system. Then, the aggregate grade (i.e., low, medium, high) relies on the lowest factor approach.

is inexpensive (e.g., cleaning and sorting), enhancing test-weight and moisture require additional investment in inputs and practices. The differences may also reflect the absence of a price premium for these unobservable dimensions, reducing farmers' incentive to upgrade quality in these areas. It can also come from farmers' unawareness about unobservable attributes.

Figure 5 investigates the correlation between observable (i.e., purity) and unobservable (i.e., test-weight, moisture) quality attributes. A high correlation would imply that farmers or traders can rely on observable attributes to (partly) infer the level of unobserved ones (Barzel, 1982). However, no strong relationship can be observed in Figure 5, such that farmers and traders cannot rely on purity to estimate test-weight or moisture level.[15]

[15]The correlation coefficients between purity and unobservable attributes are 0.18 and 0.22 and significant at 5% level for moisture content and test-weight, respectively. The literature seems to consistently suggest that correlations below 0.2 and 0.25 are at most very weak and weak, respectively (Evans, 1996).

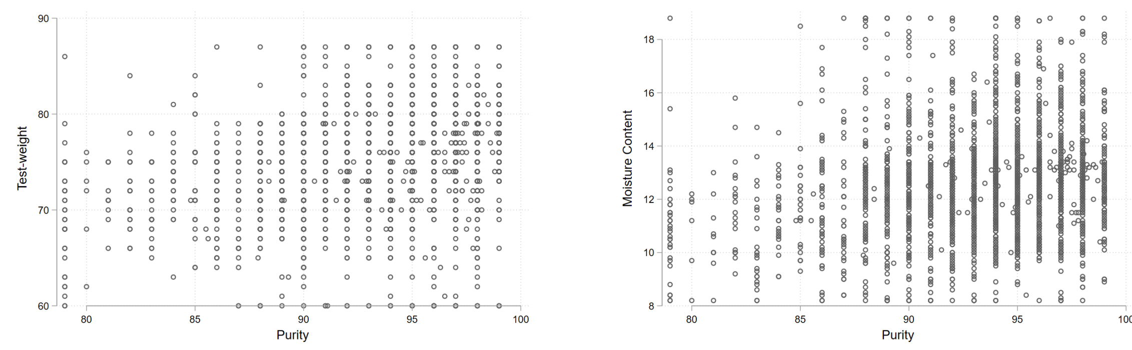
Figure 4. Quality distribution by criteria



A. Test-weight B. Moisture content C. Purity content

Source: Author's computations based on 2019/2020 wheat growers' survey.
Notes. The figures represents quality distribution for each quality criteria with vertical lines representing the threshold for different quality grades. For test-weight: low grade is for values between the two left vertical lines; medium grade is for values between the two right vertical lines; high grade is for values higher than the rightmost line. For purity content: low grade is for values smaller than the leftmost line; medium grade is for values between the two right lines; high grade is for values higher than the rightmost line. For moisture content: wheat is considered as no grade if the result is on the right of the vertical line.

Figure 5. Relationship between unobservable and observable characteristics



A. Test weight and Purity content B. Moisture content and Purity content

Source: Author's computations based on 2019/2020 wheat growers' survey.
Notes. The figure represents the relationship between observable (i.e., purity) and unobservable quality attributes in each wheat sample. Panel A. shows the relationship between purity content and test-weight. Panel B. shows the relationship between purity content and moisture content.

Next, I investigate the relationship between quality and productivity, as one may suspect a trade-off, at farmer-level, between quality and quantity. For instance, are farmers more likely to supply larger volumes as opposed to higher quality if traders do not pay a premium for high-quality wheat. While I find a weak 15% correlation (but significant at 1%) between productivity and moisture content (Figure B.8B), this not the case for test-weight (3% and non significant correlation). The findings suggest that farmers tend not to specialize in either high-quality or high-volume production.[16]

I then examined farmers' own assessment of the quality of their produce and compare it with the objective estimates. As seen in Table 3, only 28% of farmers accurately estimated the quality of their output: 26% underestimated it, and 46% overestimated it. Thus, in line with Anissa et al. (2021), farmers are somewhat, but only imperfectly, aware of the quality of their produce. Two reasons may explain this gap. First, farmers rely on an incomplete vector of mainly observable quality attributes for their assessment. Second, farmers perceived the enumerators as government agents and so overrated their products to satisfy them.[17]

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 computations based on 2019/2020 wheat growers' survey.
Notes. This table shows farmers' quality prediction accuracy according to their subjective quality assessment. Subjective quality is individual perception about the wheat quality sold on the interview day. Prediction is a categorical variable capturing farmers' prediction accuracy: it is equal to accurate if farmer's subjective measure is equal to the objective quality measure; equals under estimation if a farmer underestimates its quality (e.g., says low quality while true quality is medium); equals over estimation if a farmer overestimates its quality (e.g., says medium quality while true quality is low).

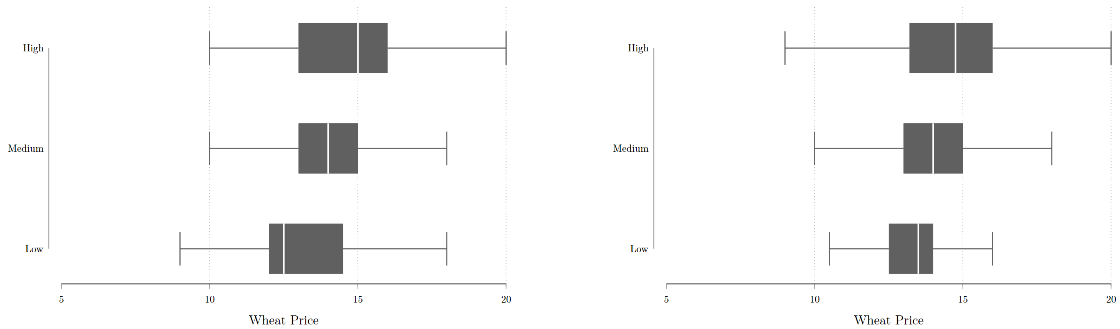
Last, I compare the effective market price farmers obtained by overall objective and subjective grade. As Figure 6 shows, market prices are positively correlated with both

[16] However, these results should be taken with caution due to potential non-classical measurement errors in farmers' plot size estimation. See for instance Carletto et al. (2013) and Abay et al. (2019) for recent studies on measurement errors about the inverse size-productivity relationship in low-income countries agriculture.

[17] In line with a social desirability effect.

objective and subjective aggregate quality assessment. The figure shows greater price dispersion for objectively higher quality wheat than for lower quality.

Figure 6. Price (in Birr/kg) by objective and subjective quality



A. Subjective quality

B. Objective quality

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

Notes. This figure shows the transaction price (in Birr/kg) distribution across quality levels. Panel A. relies on farmers' subjective assessment. Panel B. is based on laboratory test measurement. The objective classification relies on three criteria: flour extraction rate (test-weight), moisture content, and purity content to obtain objective quality measure for each. Each of these dimensions was graded on a three-point scale based on the government's official grading system. Then, the aggregate grade (i.e., low, medium, high) relies on the lowest factor approach.

6. Empirical strategy

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

6.1. Econometric approaches

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

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

where Y_{ijkt} is the wheat price per kg obtained by farmer i in market j located in *woreda* k at time t. $Quality_{ijkt}$ represents the overall wheat quality measure of farmer i in market j in *woreda* k at time t. In addition, I rely on a normalized inverse-covariance weighted summary index (Anderson, 2008) to obtain a continuous aggregate quality measure. Vector X_{ijkt} includes farmer-level variables (i.e., age, gender, yearly wheat production, wheat plot area, travel time to market, wheat type, quantity sold on market day), and the vector X'_{jkt} includes market-level characteristics characteristics (e.g., the overall volume traded) at time t. The terms γ_j and μ_t are market and time (i.e., survey week) fixed effects, respectively. Standard errors ϵ_{ijk} are clustered at the *woreda* level.[18] The primary null hypothesis to be tested is whether $\beta_1 = 0$: price do not vary with wheat quality.

Next, I measure the price-quality relationship for every quality attributes using the following equation:

$$lnY_{ijkt} = \lambda_0 + \lambda_1 Q_{ijkt} + \lambda_2 X_{ijkt} + \lambda_3 X'_{jkt} + \gamma_j + \mu_t + \epsilon_{ijk} \tag{2}$$

where vector Q_{ijkt} includes quality attributes (i.e., purity level, moisture content, and test-weight) of farmer i wheat in market j in *woreda* k at time t. The primary null hypothesis to be tested is whether $\lambda_1 = 0$: price do not differ by wheat quality attributes.

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

[18] Following recommendations by Abadie et al. (2017), standard errors are clustered at woreda level, which corresponds to the sampling process level.

$$lnY_{ijkt} = \beta_0 + \beta_1 \text{Attribute}_{ijkt} + \beta_2 C_{jkt} + \beta_3 (\text{Attribute}_{ijkt} \times C_{jkt}) + \beta_4 X_{ijkt} + \beta_5 X'_{jkt} + \gamma_j + \mu_t + \epsilon_{ijk} \tag{3}$$

where C_{jkt} corresponds to the market condition at period t. $Attribute_{ijkt}$ represent a given quality attribute (i.e., purity level, moisture content, and test-weight). The primary null hypothesis to be tested is whether $\beta_3 = 0$: the relationship between price and quality does not depend on market conditions.

However, most of the market conditions are quite plausibly endogenous. For instance, the presence of cooperatives or the market type are likely to be an outcome of past agricultural policies; a farmer's decision to use an alternative to the standard market transaction process depends on unobserved factors and can also affect the return to quality. Related biases in the estimated parameters cannot be eliminated for market alternatives for at least two reasons. First, they can have long-term effects and spillover on farmers' marketing and agricultural performance, and on market transactions. Second, no administrative data or data on the previous marketing season is available to control for non random choices in infrastructure provision. Hence, the interpretation of the corresponding parameter estimates is limited to that of correlations.

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

To identify the causal effects of market competition on market price, I rely on the occurrence of holy days on market day and pre-week and market day rainfall as instruments for market-day competition in Two-Stage Least Square framework. Religious days in Ethiopia are frequent and widely attended (Prunier, 2015). While there are 9 religious days officially recognized, it is widely accepted to take days off around the most important ones such as *Fasika* or *Eid al-Fitr*.[19] Market sales are a source of cash for farmers, thus religious days may increase their participation in markets to finance these celebrations (e.g., to buy specific food items). As market occurs only during morning, religious celebrations are unlikely to prevent farmers participation.

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

I employ a simultaneous two-stage least squares approach, where market competition is instrumented by whether the market day occurred on a holy day or on a rainy day, and whether heavy rainfall (i.e., over 10mm) fell in the previous 7 days. Wheat price heterogeneity is then regressed on the predicted value of market competition and the interaction of quality and predicted competition as:

$$\text{1st Stage}: C_{jkt} = \theta_0 + \theta_1 Z_{jkt} + \theta_2 (Z_{jkt} s \times \text{Attribute}_{ijkt}) + \theta_3 X'_{jkt} + \gamma_j + \mu_t + \phi_{ijk} \tag{4a}$$

$$\text{2nd Stage}: lnY_{ijkt} = \beta_0 + \beta_1 Attribute_{ijkt} + \beta_2 \hat{C}_{jkt} + \beta_3 (\text{Attribute}_{ijkt} \times \hat{C}_{jkt}) + \beta_4 X_{ijkt} + \beta_5 X'_{jkt} + \gamma_j + \mu_t + \epsilon \tag{4b}$$

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

[19] Five of them are Orthodox holidays: *Genna* on January 7th, *Timkat* on January 19th, *Siklet* and *Fasika* in spring, and *Meskel* on September 27th and 28th. Four of them are Islamic holidays and are moveable: *Ramadan*, *Mawlid*, *Eid al-Fitr*, and *Eid al-Adha*.

6.2. Machine learning approaches

I extend the analysis of the quality-price relationship using a predictive model based on machine learning (ML) methods.[20] ML methods are typically better suited than econometric models when dealing with unconventional data or for the test of economic predictions in low-dimensional settings (Mullainathan and Spiess, 2017). On the other hand, they are more limited with respect to causal identification of parameters (Athey and Imbens, 2019; Mullainathan and Spiess, 2017). ML data-driven approaches do not rely on pre-specified parametric approaches resulting in functional form misspecification, but instead learn the relationship between variables directly from the data and optimally choose the parameter estimates over a broad set that is specific to the data.

I apply random forests (RF) and eXtreme Gradient Boosting (XGB) to predict wheat price in Birr per kg and to select the most accurate predictors.[21] I select these algorithms as they are more interpretable than Neural Networks, more versatile than Support Vector Machines, and repeated sampling makes them more accurate (Athey and Imbens, 2019). I follow standard procedures to estimate the models.[22]

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

SHAP values correspond to the unexplained part of the model for each observation, and the sign of predictors are the association with the response.[23] A positive (negative) SHAP

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

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

[22]To estimate the ML model, the features were standardized to ensure that their scale did not influence the feature's importance. The data were then randomly split into training (70%) and test samples (30%) using five-fold cross-validation during training. Next, the wheat price for farmers in the 30% test sample was predicted and the relevant statistics computed (e.g., out-of-sample mean squared error and R-squared). Finally, a grid search was conducted over a range of parameter values during model training, selected to minimize errors.

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

value indicates an increase (decrease) in the overall average predicted response due to the inclusion of a specific feature. A null SHAP value means no deviation from the average mean prediction. In other words, it corresponds to the feature's contribution to the difference between the current and the average prediction. Thus, the higher an absolute SHAP value, the more important the corresponding feature is for the model.

7. Results

In this section, I consider four different cases. First, I test whether the quality measures described in Section 5 are recognized in the market by a premium price. Second, I estimate the heterogeneous effect of quality attributes on price when interacted with market-based conditions. Third, I estimate whether alternatives to standard market transactions can help to enhance quality recognition. Finally, I use machine learning methods to identify the most important predictors of price.

7.1. Quality price premium

7.1.1. Overall grade

I first present results related to quality recognition using objective and subjective quality measures (equation 1). Table 4 shows the presence of a price premium for high-quality wheat using overall quality measures.

Columns (1) to (6) show consistently positive and significant associations between quality and market price, although the introduction of market and time fixed effects in columns (2), (4), and (6) significantly reduce the point estimates. In the most conservative estimates, I find a 2% price premium for objective high-grade compared to low-grade wheat (column 2), a 1% premium for a 1 standard deviation increases in quality index (column 4), and an 8% premium for subjective high-grade wheat in column (6). Overall, these results suggest that farmers supplying higher quality output do receive a higher price. These findings contrast with recent experimental ones in the Ugandan maize markets by Bold et al. (2022). They show that there is a lack of demand for high quality maize in the local markets. More precisely, while they provide evidence that providing services packages raised maize quality, traders did not pay higher prices for better quality products. However, the results from Table 4 do suggest minor differences in price premium between high and medium quality wheat. This may be the result of the aggregation of different quality attributes, which could hide the actual price returns of each of them individually. I am examined these below.

Table 4. Market price premium by objective and subjective quality

	(1)	(2)	(3)	(4)	(5)	(6)
Objective quality:						
High	0.07***	0.02***				
	(0.02)	(0.00)				
Medium	0.03*	0.01*				
	(0.02)	(0.00)				
Quality Index			0.02**	0.01*		
			(0.01)	(0.00)		
Subjective quality:						
High					0.12***	0.08***
					(0.03)	(0.01)
Medium					0.08***	0.07***
					(0.02)	(0.01)
Constant	3.10***	2.41***	3.16***	2.42***	2.83***	2.55***
	(0.22)	(0.09)	(0.21)	(0.09)	(0.21)	(0.03)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Market FE	No	Yes	No	Yes	No	Yes
N	2901	2901	2856	2856	1676	1676
F-test (High = Medium)						
p-value	0.01	0.20			0.02	0.01

Notes. Price is expressed in logarithmic form. Low quality is considered as the value of reference. Quality index is the inverse covariance weighted summary index of quality attributes (i.e., purity, moisture , and test-weight) and increases with higher wheat quality. Controls included: age of farmer i, gender of farmer i, yearly wheat production of farmer i, plot size of farmer i, travel time of farmer i to market j, type of wheat produced by farmer i, quantity sold by farmer i, and market day volume traded on market j. Standard errors (in parentheses) are clustered at *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

7.1.2. Quality attributes

The extent to which an attribute can be observed may play an important role in its recognition in the market (Abate and Bernard, 2017; Fafchamps et al., 2008; Hoffmann and Gatobu, 2014). While it is possible to assess the quality of different crop attributes, testing requires lab equipment. Since a homogeneous volume of grain is needed for the test, the per kg cost of testing decreases with the overall volume of grain to be assessed. Thus, objective quality testing is rarely performed in local markets (Abate et al., 2021), though they are routinely performed at millers' levels, usually per unit of 5t of wheat (corresponding to the standard "Isuzu" truck load in rural Ethiopia). Using tested samples that we obtained from farmers, I am able to assess the extent to which unobservable quality is accurately perceived by farmers and rewarded by the market.

Using equation (2) I estimate the relationship between market price and objectively measured quality attributes. I present the results in Table 5. The results fit well with the assumptions developed in my conceptual framework in Section 3. Of the three attributes, only purity (the easier to observable) is valued by traders (column 1). The estimated coefficients are smaller but remain significant after introducing market and time-fixed effects in column (2). On average, a 1% increase in purity is associated with a 14% price premium—equivalent to 7 Birr/kg. In comparison, there is no reward for quality attributes that are harder to observe, whether moisture content or flour extraction rate. Thus, results from Table 5 show that only the observable attribute is rewarded in markets by a price premium.

These results are well aligned with those of other studies in Sub-Saharan Africa. In Benin, Kadjo et al. (2016) find a 3% lower price for insect-damaged maize. In Kenya, Hoffmann et al. (2013) measure an observable quality attribute, discoloration, and an unobservable quality attribute, aflatoxin content. They find that maize prices are strongly correlated with maize discoloration, but not with aflatoxin concentration. In Ethiopia, Abate and Bernard (2017) used test-weight as an indicator of wheat quality. They find that the average price Ethiopian wheat farmers receive does not depend on test-weight level. More broadly, the findings in the present study contribute new evidence to the recent literature on demand-side constraints for quality-upgrading. In line with Fafchamps et al. (2008), attributes measurable without cost are neither valued on markets, nor by farmers themselves. These results speak also at a wider scale than output markets. In Tanzania, Michelson et al. (2021) focus on local input market and find that market prices are orthogonal to observable and unobservable input quality.

Table 5. Market price premium for different quality attributes

	(1)	(2)
Purity	0.46***	0.14***
	(0.14)	(0.04)
Moisture	-0.02	0.01
	(0.06)	(0.02)
Test-weight	0.05	0.01
	(0.06)	(0.02)
Constant	0.87	1.76***
	(0.75)	(0.25)
Controls	Yes	Yes
Time FE	No	Yes
Market FE	No	Yes
Number of *woredas*	30	30
N	2712	2712

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

7.2. Market-based transactions

Next, I estimate equation (3) to examine whether price premiums vary with market-based conditions. I consider two market-based conditions in particular: the type of market (i.e., district and secondary markets) within the *woreda* and the level of competition on the given market day. The results are presented in Table 6 and show a significant and positive interaction between market type and test-weight on the price farmers obtained. Accordingly, a 1% increase in test-weight is associated with an 11% higher price, but only in district markets, not in secondary ones. In comparison, while there is a positive price premium for wheat purity, there are no apparent differences across market types. Last, I find no evidence of a relationship between moisture content and prices, on either types of markets.

Existing work on quality recognition in crop markets typically finds no price premium for unobservable attributes (Abate and Bernard, 2017; Fafchamps et al., 2008; Hoffmann and Gatobu, 2014; Hoffmann et al., 2013). Similarly, existing randomized controlled trials find that promoting information about unobservable attributes has a positive impact on price premiums (Abate and Bernard, 2017; Bernard et al., 2017). However, these past studies only consider a single market type. My results show a difference in quality recognition for test-weight between district and secondary markets, suggesting greater buyer interest of this attribute in district markets. It does not however necessary imply easier recognition of this attribute in district markets, a point I return to below.

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

Quality variable:	(1) Purity	(2) Moisture	(3) Test-weight
Quality	0.12**	0.03	-0.01
	(0.05)	(0.03)	(0.02)
District Market × Quality	0.09	-0.03	0.11**
	(0.11)	(0.03)	(0.05)
Constant	2.55***	2.37***	2.23***
	(0.03)	(0.10)	(0.13)
Control	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Market FE	Yes	Yes	Yes
Number of *woredas*	30	30	30
N	2725	2856	2731

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

Next, I consider the relationship between competition level (number of traders per farmer) and quality recognition. This is important as traders' market power can lead to major constraints in investment decisions and quality upgrading (Swinnen and Vandeplas, 2015; Swinnen and Vandeplas, 2010). Where traders' market power is high, traders have no incentive to reward quality as farmers have limited outside options. In turn, a larger number of traders per farmer may result in a broader diversity of traders, including those with a higher valuation of higher-quality wheat. However, the existing literature in low-income countries on the topic mainly refers to global and export-oriented supply chains (Reardon and Hopkins, 2006; Swinnen and Vandeplas, 2010). Competition in local markets has also seen a recent rise in academic interest (Bergquist and Dinerstein, 2020; Dillon and Dambro, 2017). While Dillon and Dambro (2017) do not find lack of competition in agricultural markets in SSA, Bergquist and Dinerstein (2020) provide new experimental evidence on imperfect competition among intermediaries from maize markets in Kenya. Given that local markets remain the principal option for farmers to sell their output, it is helpful to measure the extent to which market competition plays a role in quality recognition. For instance, Abate and Bernard (2017) find that Ethiopian wheat growers usually sell and buy food in their local *kebele* market and may therefore be captive to traders.

Table 7 shows how the relationship between price and quality differs with competition. Columns (2), (3), and (4) of Table 7 show that greater demand-side competition is positively correlated with market price premium, albeit average prices are lower in the most competitive markets.

However, as discussed in Section 6, there is concern with respect to the validity of the exogeneity assumption between market competition and price. Thus, I rely on a 2SLS strategy to establish identification based on three instruments: occurrence of religious days, whether it rained in the pre-market week, and whether it rained on the market day. The interaction term which captures the heterogeneous effect of competition on quality price premium is also endogenous. Hence, I include interaction terms between instruments and quality attributes as additional instruments (Wooldridge, 2010). I first assess whether the instruments used are good predictors of competition. The results in Table C.6 show that rainfall and occurrence of a religious day have a significant and negative effect on market day competition. The F-statistic of the first-stage regression associated with a test of the null hypothesis that all coefficients are zero is reported in Table 7. The F-statistic exceeds the Staiger and Stock (1997) rule-of-thumb value of 10 in the primary estimation in Column (4), indicative of non-weak instruments. Apart from purity in Column (6), the F-statistic exceeds 10 in other estimates, indicating that the instruments are good predictors of competition. As I define market day competition as the number of traders per farmer, the negative relationship may be due to higher farmer participation or lower trader participation. The results in Table C.4 show that religious days and rainfall have a positive and significant relationship with farmers' participation, possibly suggesting that farmers may sell more on a religious day to finance religious expenditure. The number of farmers in the market is higher when rainfall occurs pre-week and on market days, in all likelihood in a bid to sell wet wheat to prevent loss from rot. However, only rainfall during the week before market day has a significant and negative relationship on traders' participation. This supports the idea that some traders do not go on the following market day to avoid any additional costs related to the purchase of wet wheat (e.g., storage or screening costs).

Columns (1) and (5) of Table 7 show that higher demand-side competition is negatively correlated with market price, even though not significantly so after accounting for endogeneity. While this result contradicts theory basic economic theory, the farmer-trader transaction is only the first in the value chain. Greater demand-side competition at this stage implies greater supply-side competition when traders sell their output to the next value-chain actor (i.e., miller, broker). Traders may obtain a lower selling price in this context and, as a result, pay a lower price to farmers.

Accounting for endogeneity in competition considerably affects the results. As reported in Table 7, 2SLS estimates point to larger price premium for purity and moisture content, as compared to OLS estimates, whereas the effect of test-weight becomes insignificant. In addition, the size of the interaction terms coefficient more than triples in 2SLS estimates in Columns (6) and (7) compared to OLS estimates in Columns (2) and (3).

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

These results align with Bold et al. (2022), who find that the entry of buyers rewarding high quality increases the equilibrium price. In contrast, Bergquist and Dinerstein (2020) find that new entrants will not modify the market environment where pre-existing traders have significant market power as they will join collusive agreements with the incumbents.

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

Table 7. Price premium for different quality attributes, with heterogeneity by market competition

	OLS				2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quality variable:	None	Purity	Moisture	Test-weight	None	Purity	Moisture	Test-weight
Quality		0.06	-0.01	-0.01		-0.28	-0.08	0.06
		(0.04)	(0.01)	(0.02)		(0.18)	(0.05)	(0.09)
Competition	-0.14*	-3.80**	-0.95**	-1.31***	-0.14	-17.73**	-2.87**	2.23
	(0.08)	(0.33)	(0.37)	(0.30)	(0.14)	(8.37)	(1.40)	(4.08)
Competition × Quality		0.80**	0.31**	0.26***		3.82**	1.01*	-0.60
		(0.33)	(0.13)	(0.08)		(1.84)	(0.54)	(0.96)
Constant	2.58***	2.31***	2.57***	2.59***	2.62***	2.61***	2.70***	2.54***
	(0.02)	(0.22)	(0.09)	(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	2726	2856	2731	3444	2726	2856	2731
F statistics (First stage)								
Competition					11.99	6.11	13.87	10.19
Interaction term						6.11	13.43	10.09
Overidentification p-value					0.06	0.54	0.21	0.37

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

7.3. Alternatives to standard market transactions

Results thus far suggest that, as a decentralized allocation mechanism, the market fails to reward unobservable attributes with a price premium. Fafchamps (2003) states that formal institutions in SSA are inefficient due to small transaction size. As a result, market actors may use alternative mechanisms to ensure quality provision. These mechanisms can be formal, such as providing agricultural inputs through cooperatives (Bernard et al., 2013; Deutschmann et al., 2020), certification services (Bernard et al., 2017), vertical integration (Deutschmann et al., 2020), or informal arrangements, such as farmer-trader relationships based on trust and repeated interactions (Casaburi and Reed, 2022; Fafchamps and Minten, 1999).

I examine these issue using three variables: personalized relationship between traders and farmers, existence of a mill nearby the market site, and existence of a wheat producer cooperative in the market. Each variable captures a slightly different aspect of farmers' alternatives to market. First, the farmer-trader relationship emerges as a credible alternative to minimize contract breach risk (Fafchamps, 2001). Without protection against opportunistic behavior, constructing personal trust through repeated interactions is often a reliable substitute to market allocations. While Fafchamps and Minten (1999) argues and find that quality provision is not central in a relationship, Macchiavello and Morjaria (2021) shows in the Rwandan Coffee value chain that relational contracting is used to sustain quality supply. Closer to my context, Anissa et al. (2022) find that wheat farmers involved in relational contracting supply higher quality output. I intent to delve further, by considering whether farmers supplying higher quality wheat receive a price premium, depending on their relationships with traders. Second, value chains, like the wheat value chain in Ethiopia, can be long and involve a large number of intermediaries (Osborne, 2005). The presence of intermediaries increases final costs as each agent expects to make a profit. However, intermediaries are not the final buyers of the goods, and their demand for quality only depend on that of downstream value chain actors. For example, millers are the main end-buyers of wheat before its transformation into flour. Their demand is largely driven by quality, as purity, moisture, and flour-extraction rate (test-weight) significantly affect the volume and quality of flour. Thus, the presence of a mill near local markets is expected to reduce the length of the value-chain and to result in higher price for higher quality wheat. Finally, I investigate the relationship between returns to quality and the presence of cooperatives near the market site. From field observations, cooperatives are often interested in higher-quality wheat that they aggregate under the cooperative's brand name. A number of them assess the quality of individual farmer's wheat before aggregating with others'. From a farmer's perspective, however, selling to a cooperative has drawbacks in that payment is often made with a month's delay.

Table 8. Price premium for different quality attributes, with heterogeneity by alternatives to standard market transactions

Quality variable:	(1) Purity	(2) Moisture	(3) Test-weight	(4) Purity	(5) Moisture	(6) Test-weight	(7) Purity	(8) Moisture	(9) Test-weight
Quality	0.16**	0.05**	-0.01	0.10	0.04	-0.02	0.03	-0.03	-0.01
	(0.07)	(0.02)	(0.03)	(0.06)	(0.03)	(0.02)	(0.06)	(0.02)	(0.03)
Relationship	0.13	0.11*	-0.19						
	(0.36)	(0.06)	(0.21)						
Relationship × Quality	-0.03	-0.04*	0.05						
	(0.08)	(0.02)	(0.05)						
Millers × Quality				0.08	-0.04	0.10**			
				(0.08)	(0.04)	(0.04)			
Cooperatives × Quality							0.17**	0.08**	0.07*
							(0.08)	(0.03)	(0.04)
Constant	2.55***	2.38***	2.51***	1.77***	2.44***	2.37***	1.85***	2.35***	2.24***
	(0.03)	(0.06)	(0.14)	(0.22)	(0.05)	(0.09)	(0.24)	(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	2726	2856	2731	2726	2856	2731	2726	2856	2731

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

Table 8 shows the heterogeneous price premium for each quality attribute by alternatives to standard market transactions. The effect of the farmer-trader relationship is first investigated, through the survey question: "Did you sell your wheat to your usual trader?". In theory, such informal contract farming can provide a commitment mechanism to resolve the asymmetric information issue. However, I do not find these effects. If anything, in column (2), I find that if markets reward moisture content at a low rate, the premium is null for farmers with a long-term relationship with their buyer.

The second aspect of alternatives to traditional marketing is the presence of nearby millers. The findings are presented in Columns (4) to (6). No additional rewards are paid upon the presence of a nearby miller for moisture and purity attributes. In contrast, results in Column (6) point to a positive reward for unobservable quality (test-weight) with the presence of a nearby mill. In these markets, a 1% increase in test-weight score leads to a 10% price premium. In Ethiopia, millers pay significant attention to flour-extraction rate. Two bundles of wheat, identical in terms of observable attributes (e.g., purity), may exhibit significant differences in flour-extraction rate, thereby affecting millers' final profit (Abate and Bernard, 2017). The presence of an on-site mill may affect rewards to such attributes through both informational effects and reductions in the length of the value chain that otherwise dilute the incentive to procure higher quality wheat.

Lastly, the results in columns (7) to (9) of Table 9 show a positive effect of the presence of a cooperative on price rewards for all the quality attributes, whether observable or unobservable. On average, when there is a cooperative, a 1% increase in quality is associated with a price premium of 17% for purity, 8% for moisture, and 7% for test-weight. Cooperatives play a substantial role in rural markets by providing fertilizers and seeds on credit (Bernard et al., 2008; Deutschmann et al., 2020). Hence, farmers with access to cooperatives in the market may benefit from such agricultural technology and produce higher quality wheat. Indeed, 89% and 60% of Ethiopian farmers with access to cooperatives purchase fertilizers and seeds, respectively (Abate and Bernard, 2017). In Ethiopia, cooperatives usually provide quality assessments when they collect output. Once aggregated, cooperatives may either resell bulked wheat to millers or produce flour themselves. It is worth mentioning that selling output through a trader is the main marketing channel (Minot et al., 2019), and that if any selection had occurred, higher quality farmers would have chosen the spot market instead of the cooperative (Abate and Bernard, 2017). These results may inform the role that cooperatives can play in upgrading quality in local markets.

7.4. Geographic conditions and marketing time

7.4.1. Market location characteristics

Several studies in SSA show that the geographic location of rural markets affects equilibrium prices (Aker, 2010; Minot et al., 2019; Vandercasteelen et al., 2018). Here, the question is examined using geographic and demographic variables related to market environment. Each variable captures a slightly different dimension. The first is based on the market's physical distance from Addis Ababa, the main demand center. The second captures captures the potential link between market price and population density (Bernard et al., 2008). In the most densely populated *kebele*, markets might be better integrated into the regional or national wheat market. These areas also derive substantial benefits from their positions in terms of economies of scale, which can reduce transaction costs. Areas with higher population density are also likely to be more urbanized and thus be subject to greater demand for quality (Vandercasteelen et al., 2018).

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

7.4.2. Marketing time

Many smallholder farmers must deal with liquidity issues at harvest time to pay back agricultural loans or satisfy essential needs such as food or school fees (Dillon, 2020; Stephens and Barrett, 2011). Moreover, without access to affordable and efficient storage technology, stored outputs may suffer severe damages from fungi, rodents, mold, and insects. For these reasons, price premium on various quality attributes may differ across the dates of the survey rounds from which the data were obtained. The results are presented in Table 10. Overall, I find only limited evidence that the transaction date is associated with differential rewards to quality. The results in column (1) suggest that traders pay a price premium for the purest wheat supplied. However, purity is not rewarded later in the commercialization season. This closely aligns with earlier work by Kadjo et al. (2016) on the rural maize sector in Benin.

Table 9. Price premium for different quality attributes, with heterogeneity by locating markers

	(1) Purity	(2) Moisture	(3) Test-weight	(4) Purity	(5) Moisture	(6) Test-weight
Quality	0.07	0.01	-0.01	0.07	0.05	-0.18*
	(0.07)	(0.03)	(0.02)	(0.25)	(0.07)	(0.11)
Addis Ababa × Quality	0.11	0.03	0.11*			
	(0.09)	(0.03)	(0.06)			
Population Density × Quality				0.01	-0.01	0.04*
				(0.04)	(0.01)	(0.02)
Constant	1.86***	2.37***	2.23***	1.73***	2.37***	2.21***
	(0.24)	(0.10)	(0.15)	(0.10)	(0.14)	(0.14)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2726	2856	2731	2726	2856	2731

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

7.5. Robustness check

It is possible, of course, that some *woredas* drive the results observed in Tables 4 and 5. For instance, price premium might be lower (higher) for observable (unobservable) characteristics in wheat producing *woredas* because of the high volume supply. To address this, I separate *woredas* into two groups based on wheat specialization. A *woreda* is specialized in wheat production if wheat is the cereal with the highest share of total cultivated land area. Table C.5 shows the results for objective quality measures. Overall, doing this does not change the overall conclusion: farmers receive a price premium for both higher quality wheat and attributes easier to observe. While the price premium paid for purest wheat is positive in both specialized and not specialized *woredas*, the coefficient is slightly lower and imprecisely estimate in the former—surely because of a smaller sample size. It is possible, for instance, that quality standards to obtain a premium are lower in unspecialized districts, as wheat production is smaller in these

Table 10. Price premium for different quality attributes, with heterogeneity by marketing period

	(1) Purity	(2) Moisture	(3) Test-weight	(4) Purity	(5) Moisture	(6) Test-weight
Quality	0.33***	0.00	0.01	0.35***	-0.01	0.09
	(0.10)	(0.02)	(0.04)	(0.15)	(0.03)	(0.12)
Follow-up	1.57**	0.01	0.03			
	(0.73)	(0.09)	(0.36)			
Follow-up × Quality	-0.33**	0.03	0.01			
	(0.16)	(0.03)	(0.09)			
Survey week				0.11*	0.03	0.06
				(0.06)	(0.03)	(0.06)
Survey week × Quality				-0.02	0.01	0.00
				(0.01)	(0.01)	(0.01)
Constant	0.89*	2.40***	2.37***	0.67***	2.30***	1.85***
	(0.49)	(0.10)	(0.22)	(0.74)	(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	2726	2856	2731	2726	2856	2731

Notes. Price, purity, moisture and test-weight are expressed in logarithmic form. 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.

districts.

In addition, I rely on the post-double selection (PDS) LASSO procedure presented in Belloni et al. (2013) to ensure that the choice of control variables did not bias the result. The main advantage of PDS is that it picks control variables consistently and avoids standard errors estimation issues. Table C.7 shows the association between quality and price, independent of market conditions as above in Table 5. As shown in Table 5, a price premium is only paid for purity. Table C.9 shows the association between price and quality by market type. The results are similar to those of Table 6. Table C.10

presents the results for the association between price and quality with heterogeneity by alternatives to market mechanisms. The results are identical to those observed in Table 5.

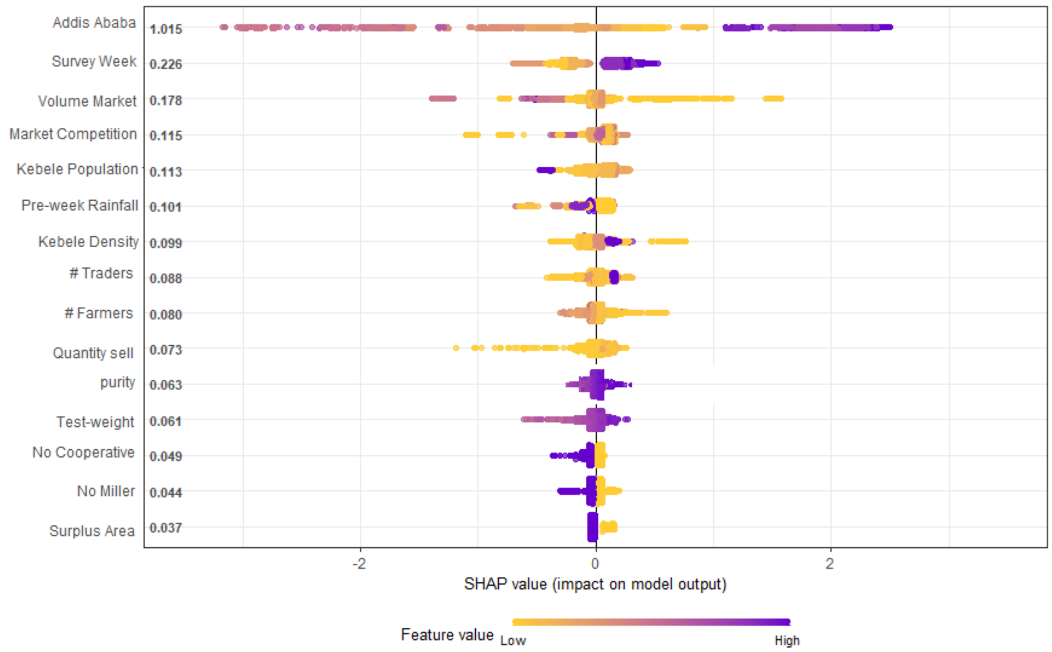
7.6. Identifying the most important price determinants, a machine learning approach

Previous work has suggested various farmer-level solutions to increase local agricultural prices (Bergquist and Dinerstein, 2020; Casaburi and Reed, 2022; Karlan et al., 2014). Often, this literature assumes that the main barriers to increasing price might be overcome at individual level. However, such interventions may have a limited impact if market conditions are the main price determinants. For instance, lack of infrastructure, limited information, and poor value-chain integration may prevent farmers from obtaining higher prices, and farmer-level intervention will do little to overcome them. Here, I examine whether wheat price is more likely to be determined by market or by farmer characteristics.

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

My aim is to determine which features are the most predictive and the direction of the association with the response. Figure 7 plots the Shapley values of the fifteen most predictive features using XGB. The SHAP values and the features are placed on the horizontal and vertical axis, respectively. Each dot represents a farmer. The average contribution of the corresponding variable in price prediction is on the vertical axis. A positive (negative) SHAP value represents an increase (decrease) in the predicted price across all possible combinations of the predictors. For instance, the “market volume” feature decreases the predicted values (the SHAP value is negative) for most observations when included in the model. Lighter colors imply smaller values of the feature: lower values of volume traded on the market are observed where SHAP is positive. However, it is not easy to fully understand the association between the feature and the predicted price from Figure 7 alone.

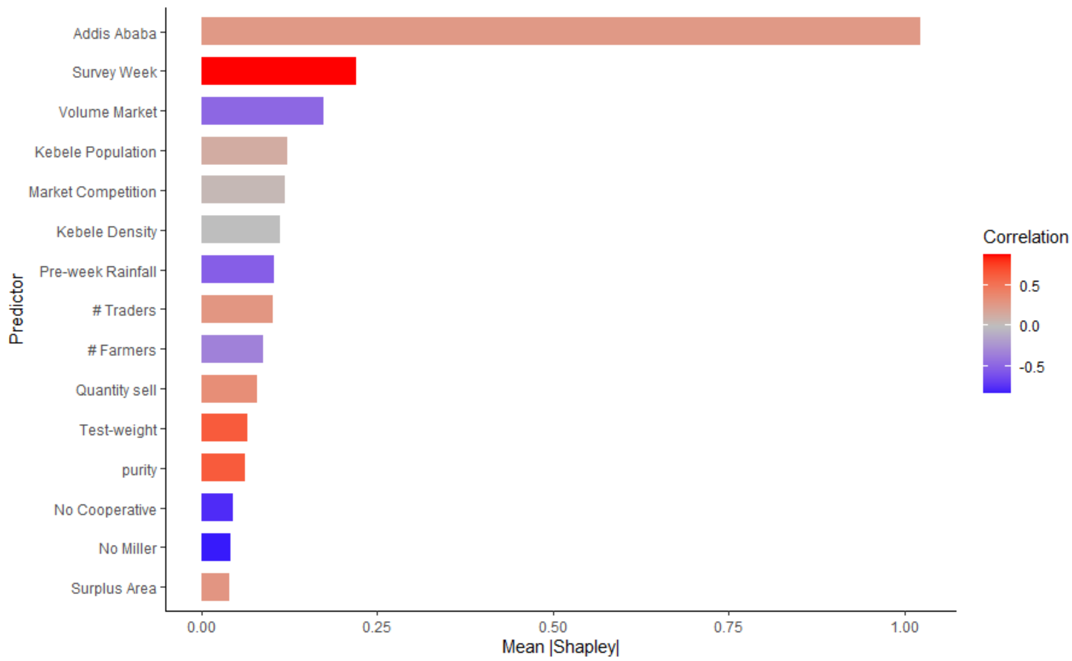
Figure 7. Shapley values of the most predictive features of wheat price: eXtreme gradient boosting model



Source: Author's computations based on 2019/2020 wheat survey.
Notes.: This Figure shows the Shapley (SHAP) values of the fifteen most predictive features using eXtreme Gradient Boosting. A positive (negative) SHAP value represents an increase (decrease) in the predicted variable (i.e., wheat price per kg) across all possible combinations of the features. The mean of SHAP values indicates the variable's average contribution in prediction on the vertical axis. Darker color corresponds to higher values of the predictor.

Figure 8 displays an astute way to visualize the association between features and predicted prices. Average SHAP values are plotted, then colored by the correlations between the feature and its SHAP values. Distance to Addis Ababa, the survey week, and the number of traders on the market day have high positive associations with wheat price, whereas the volume traded on market day, the number of farmers, and the absence of a cooperative or a miller have a negative relationship. Moreover, the quantity sold by farmers, the purity and the test-weight values are positively correlated with price. Most of the best wheat price predictors are market condition characteristics rather than farmer characteristics (i.e., quantity sold, purity, and test-weight). Otherwise, quality attributes (i.e., purity and test-weight) are among the most important price predictors. These results support previous ones, underscoring the importance of market conditions in the analyses of price premiums for quality and farmers' incentive to invest in improving the quality of their output. These warrant future research in better measuring and quantifying the potential effect of market conditions variation on quality price premium.

Figure 8. Correlation between predictive features and predicted wheat price: eXtreme gradient boosting model



Source: Author's computations based on 2019/2020 wheat survey.
Notes. This Figure 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.

8. Summary and Concluding Remarks

Food crop quality is one of the main concerns that Sub-Saharan African countries must address to improve revenues for smallholder farming and thereby contribute to reduce poverty. A large number of empirical studies have considered supply-side approaches to alleviate farmers' constraints in quality-upgrading, such as liquidity, risk, information, and technology access (De Janvry and Sadoulet, 2020). Following recent empirical papers focusing on demand-site constraints (Abate and Bernard, 2017; Bernard et al., 2017; Bold et al., 2022), the present study presents evidence that imperfect market recognition of quality must be addressed to enhance quality supply. Using original survey data collected in 60 Ethiopian wheat markets, I examined the extent to which quality is rewarded in the Ethiopian wheat market. I found that farmers imperfectly interpret the quality they supply, and are imperfectly rewarded for their higher-quality wheat. While a significant price premium is paid to farmers for purer wheat (i.e., observable attribute), I find that low moisture content and test-weight (i.e., unobservable attributes) are not rewarded. This finding is consistent with the conceptual framework that I use, and it supports the idea that quality factors for unobservable attributes are not a current concern for traders.

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

These findings are not based on a purposefully designed trial, and several of the highlighted relationships must be interpreted as exploratory. However, the results suggest that current policies proposed to alleviate farmers' constraints (e.g., technology adoption subsidies, financial services, and extension services development) are limited in promoting quality-upgrading as long as quality is not fully rewarded in the market. Given the positive correlation between market competition and quality recognition, policymakers might be interested in promoting competition to enhance price premiums for quality, which may in turn increase farmers' returns from quality-upgrading.

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

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Appendix

A. Conceptual Framework

In this section, I present a model partially based on Mitchell (2021) and Abate et al. (2021) focusing on the farmer-trader interaction on the local spot market (the first stage of the agricultural value chain).

A.1. Benchmark: quality is freely observable

Consider a risk-neutral farmer who produces one unit of a crop each season that she will sell to a risk-neutral trader on the local market. Following Lancaster (1966), demand for the crop is a function of its characteristics rather than the crop itself. Define $Q_i = \{q_i^1, q_i^2, ...q_i^N\}$ a vector of quality attributes (e.g., size, purity, extraction-rate) farmer's i crop supply. Assume that the trader values two specific quality attributes: q^o which is directly observable, and q^u which is not. For sake of clarity, the subscript i is omitted in the following analysis. Farmers can supply two possible quality levels for each quality attribute. She can either supply a crop with high level for a given attribute ($q^k = H^k$), expecting price h^k from the trader, or a crop with low level for that attribute ($q^k = L^k$), expecting to obtain price l^k (with $h^k \geq l^k > 0$). Farmers can decide to exert costly effort (c^k) to increase the quality of a specific attribute (q^k), where farmers face heterogeneous effort costs, drawn from the distribution $F(c^k)$.[24] The cost of this effort is $c^k \in \{0, \bar{c^k}\}$, with $\bar{c^k}$ the cost to produce high-quality attribute. The farmer knows the costs while the trader does not. When a farmer decides to make this effort, she produces with certainty a high-quality level of a given attribute and a low-quality otherwise.

When q^k is freely observable for farmers and traders ($q^k = q^o$), trader and farmer have the same knowledge about the quality level of this attribute (and implicitly on the cost c^o incurred to provide this observable attribute). The resulting price premium would equal the difference in crop prices with high and low quality attribute $h^o - l^o$. If the farmer supplies a crop with a high-quality level of the observable attribute ($q^o = H^o$) she will obtain the following payoff: $h^o - c^o$, and l^o if she supplies low-quality ($q^o = L^o$).

[24]Farmers are inherently heterogeneous in their capacity to produce higher quality according to natural endowments such as soil quality, and farmers characteristics such as farming experience, information constraints, or technology access.

Therefore, the farmer would decide to exert this additional effort to enhance the quality of the observable attribute (c^o) if the cost to produce higher quality is lower than the price premium she can obtain from it. Formally, the incentive compatibility constraint is:

$$h^o - l^o \geq c^o \tag{5}$$

Alternatively, the farmer can decide not to sell her crop once in the market. Assume that this outside option generates a zero payoff.

Some quality attributes are however unobservable to the naked eyes and one of the agents may support additional costs to assess its quality level. In an "imperfect institutions" context without access to third-party quality certification schemes, agents may use at least two alternative strategies to reveal quality: (i) signaling and (ii) screening. These strategies are available to either one of the agent: farmers for signaling, and traders for screening.

A.2. Farmer's cost of signaling

A crucial issue related to unobservable quality attributes in local spot markets is that a farmer's trading decision depends on privately held information that adversely affects uninformed traders. Although the farmer may not observe the unobservable quality, she knows its level with certainty based on her own characteristics and costs incurred whereas the trader does not. However, the trader knows with accuracy the level of quality for the observable attribute as it is, by definition, freely observable. If the trader expects a positive correlation between observed and unobserved quality (from farmers' characteristics and efforts), quality-level in the observable attribute becomes an indication of the quality-level in the unobservable one. Hence, the farmer can provide a high-quality level of the observable attribute as a signal for the effort she made to produce the unobservable attribute (c^u) (Spence, 1981). This signal, noted s, is equal to the true quality of the unobserved attribute with probability $\rho(r) \in (\frac{1}{2}, 1]$ and $s \neq q^u$ with probability $1 - \rho(r)$. This probability is a positive function of the degree of correlation between the unobservable and observable attributes ($r \in [0, 1]$), with $r = 0$ in the absence of correlation and $r = 1$ when the correlation is perfect. The higher the correlation between the two attributes, the higher the probability that the signal corresponds to the true quality of the unobserved attribute. In other words, with a sufficiently high degree of correlation, the observable attribute is considered a reliable proxy for the unobserved attribute. Providing this signal is costly for the farmer because she must also exert an effort to provide a high-quality level for the observable attribute. The total cost to provide a crop with a high-quality level of the unobservable attribute is now $c^u + c^o$.

If the farmer exerts additional efforts, she supplies a crop with high-quality unobservable attribute ($q^u = H^u$) and her expected payoff will be:

$$\rho(r)h^u + [1-\rho(r)]l^u - c^u - c^o$$

Conversely, if she does not make additional efforts, she supplies a crop with low-quality level of the unobservable attribute($q^u = L^u$) and her expected payoff will be:

$$[1-\rho(r)]h^u + \rho(r)l^u$$

As a result, the farmer will make additional efforts if the following incentive compatibility constraint is satisfied:

$$\rho(r)h^u + [1-\rho(r)]l^u - c^u - c^o \geq [1-\rho(r)]h^u + \rho(r)l^u$$

After some algebra, one obtains the price premium for which the farmer would be willing to exert efforts to supply a crop with a high-quality level of the unobservable attribute:

$$h^u - l^u \geq \frac{c^u + c^o}{2\rho(r)-1} \tag{6}$$

From this result, one can derive the following: when actors can use the observed attribute as a reliable proxy of a given unobserved attribute ($r = 1$) the price premium should be higher than the additional efforts ($c^u + c^o$); there is no price premium ($h^u = l^u$) when both attributes are uncorrelated ($r = 0$).

For the farmer to be willing to participate in the transaction and sell her crop, expected payoff must be greater than the (zero-valued) outside option.[25] The farmer will accept

[25]This assumption may be perceived as strong at first glance, but I assume it is quite plausible. Indeed, farmers participate in the spot market to get immediate rather than later payment. Moreover, as farmers carry their crops to the local market and incur transport costs, not selling their products may even result in a net loss. This assumption seems reasonable since only 0.1% of farmers do not sell their wheat while on the market.

to sell her crop if the following participation constraint is satisfied:

$$\rho(r)h^k + [1-\rho(r)]l^k - c^u + c^o \geq 0$$

which can be rewrite such as:

$$\rho(r)h^k + [1-\rho(r)]l^k \geq c^u + c^o \tag{7}$$

A.3. Trader's screening costs

On the trader's side, prices offered for each attribute, h^k and l^k, should align with zero expected profits and satisfy the farmer's participation constraint. Assume that traders face competitive markets and sell the output to a processor (e.g., miller) who can observe the quality attributes regardless of their degree of observability.[26] The trader receives a price corresponding to the quality of the observable attribute: P_H^k when $q^k = H^k$ and P_L^k when $q^k = L^k$. The trader is certain to receive these prices for those attributes that are observable at the time she purchased it ($q^k = q^o$). For non-observable attributes, trader relies on the quality signal obtained from the farmer. Thus, when the signal points towards high-quality, she expects to receive:

$$\rho(r)P_H^u + [1-\rho(r)]P_L^u$$

when the signal points towards low-quality, she expects to receive:

$$[1-\rho(r)]P_H^u + \rho(r)P_L^u$$

Moreover, the trader incurs sunk costs to participate in the market C_F (e.g., trucks, trading licence, wages, marketing costs) regardless of the market conditions and quality buy. She also incurs non-linear variable costs $C_V^{1-\theta}$ that differ according to the market conditions θ. Market conditions can be defined as any market characteristic that affects transaction costs such as competition, remoteness, presence of cooperatives, and others. Higher market conditions imply better infrastructures at the physical marketplace, such as having certified scales, moisture meters, and sorting tables. Market condition θ is

[26]While recent experimental evidence may suggest that crop markets are not competitive (Bergquist and Dinerstein, 2020), the current evidence broadly supports the idea that crop markets are competitive in SSA (Dillon and Dambro, 2017).

continuous and normalized such as $\theta \in]0,1]$. Cost to assess quality decreases as the market conditions improve (i.e., $\theta \to 1$) and increases as market conditions worsen (i.e., $\theta \to 0$). Therefore, for the observable attribute, the trader sets h^o and l^o such as:

$$h^o = P_H^o - C_F - C_V^{1-\theta} \tag{8}$$

$$l^o = P_L^u - C_F - C_V^{1-\theta} \tag{9}$$

For the unobservable attribute, the trader sets h^u and l^u such as:

$$h^u = \rho(r)P_H^u + [1-\rho(r)]P_L^u - C_F - C_V^{1-\theta} \tag{10}$$

$$l^u = [1-\rho(r)]P_H^u + \rho(r)P_L^u - C_F - C_V^{1-\theta} \tag{11}$$

A.4. Farmers' decision

Assuming that farmer's participation constraint is satisfied, so that she sells her crop to the trader, one wishes to identify whether or not she will incur the additional costs of producing higher quality of a given attribute. The farmer's decision to exert this effort differs for unobservable and observable attributes.

Using equations (5), (8) and (9), a farmer will make effort for the observable attribute if:

$$P_H^o - P_L^o \geq c^o \tag{12}$$

If equation (12) is satisfied, the farmer will exert effort and obtain a certain payoff $P_H^o - P_L^o - C_F - C_V^{1-\theta} - c^o$, otherwise she will not make effort and earn $P_L^o - C_F - C_V^{1-\theta}$, with certainty.

For the unobservable attribute, combining equations (6), (10) and (11) together, yields farmer's following decision rule: produce high-quality crop only if

$$[2\rho(r)-1]^2[P_H^u - P_L^u] \geq c^u + c^o \tag{13}$$

If equation (13) is satisfied, the farmer's expected payoff is:

$$2[\rho(r)-1][P_H^u - P_L^u] + P_H^u - C_F - C_V^{1-\theta} - c^u - c^o$$

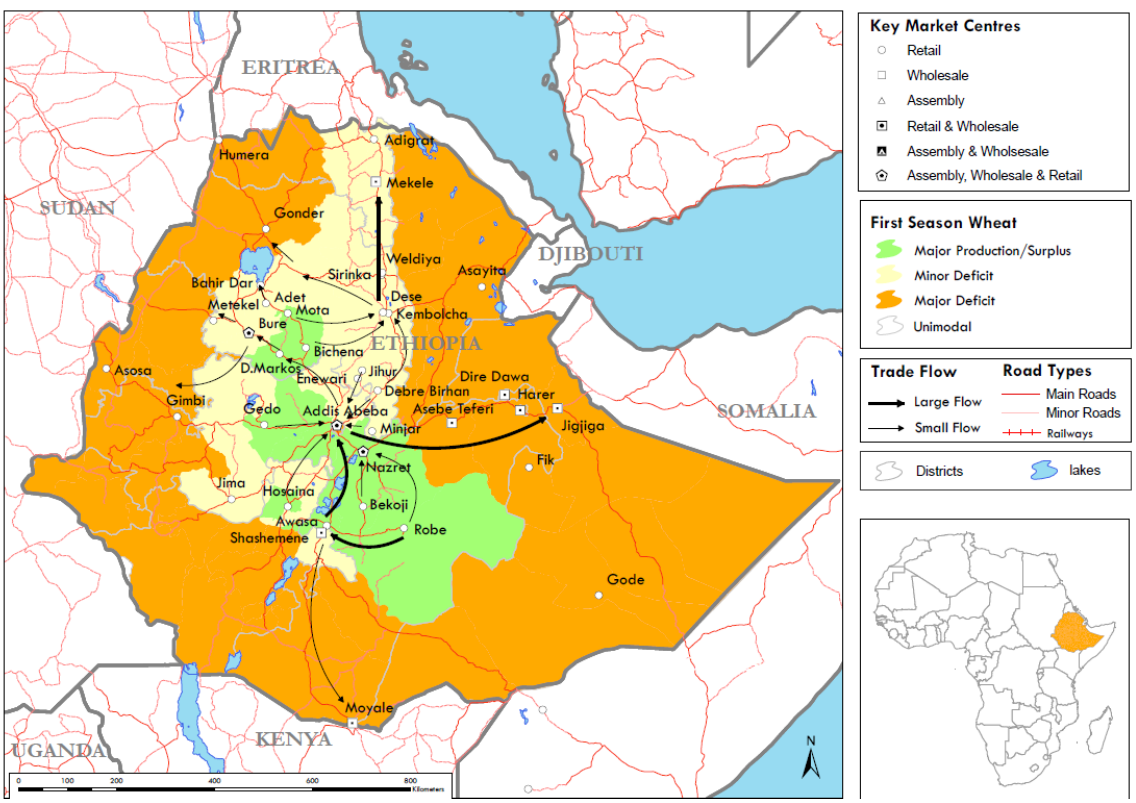
Otherwise she will not make effort at improving quality and expect to earn:

$$2[1-\rho(r)][P_H^u - P_L^u] + P_L^u - C_F - C_V^{1-\theta}$$

It is essential to highlight that the expected payoff when exerting efforts is always higher than without efforts as long as the farmer's incentive compatibility is satisfied.

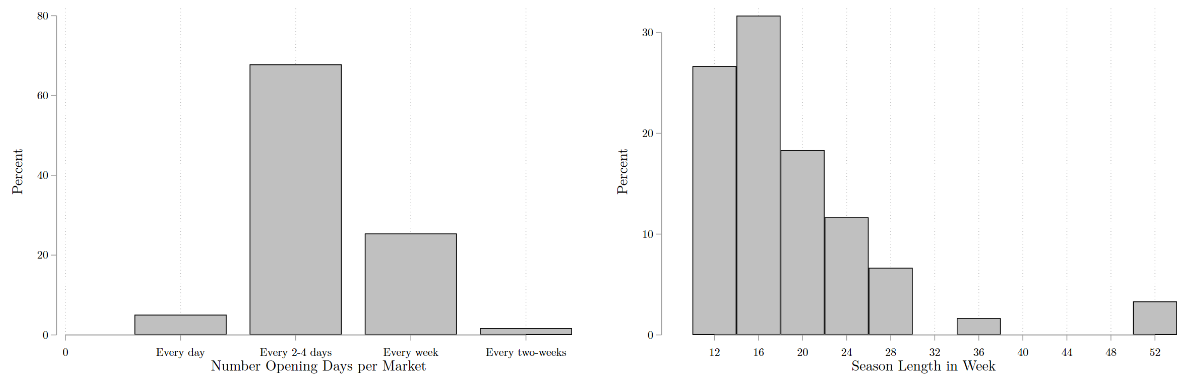
B. Figures

Figure B.1. Ethiopian wheat production and market flow in 2010



Source: FEWSNET (in FAO, 2014).

Figure B.2. Number of opening days and season length per market

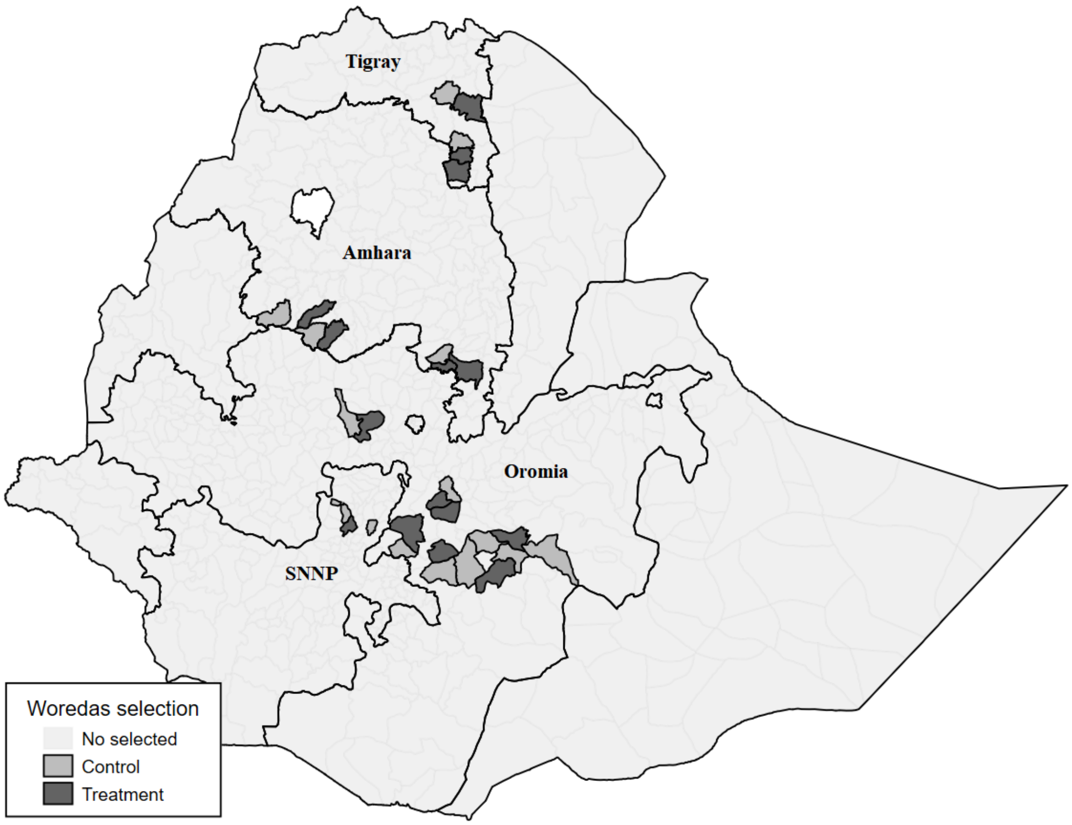


A. Number of opening days each week per market B. Season Length in weeks per market

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

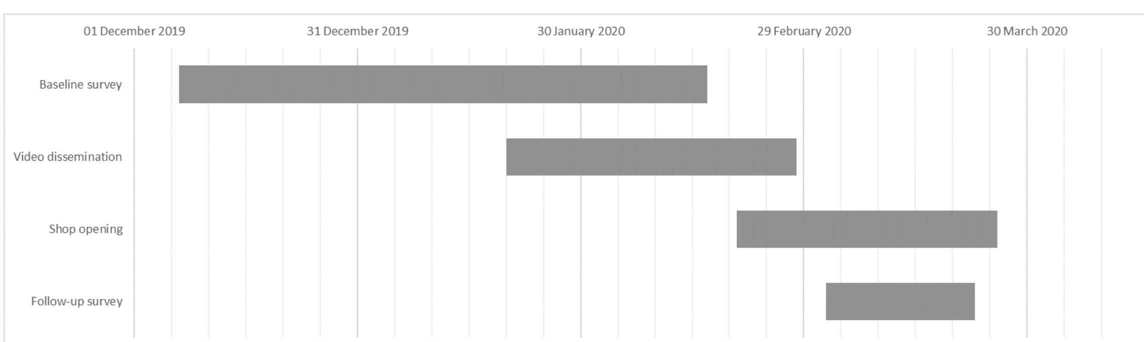
Notes. This figure shows market operation characteristics. Panel A. shows the distribution of the number of opening days each week. Panel B. shows the marketing season length, it corresponds to the number of week where actors are actively trading wheat.

Figure B.3. Study zone and initial RCT allocation



Source: Author.
Notes. The figure shows the districts where the study takes place and their initial treatment status.

Figure B.4. Timeline

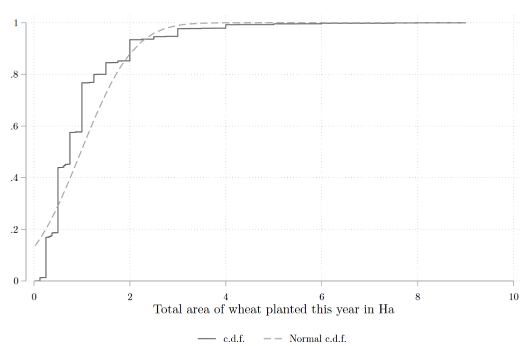


Source: Author.
Notes. The figure shows the study timeline.

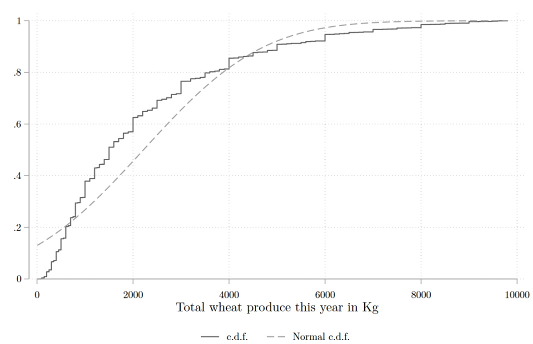
Figure B.5. Example of Facebook population map

Source: Author based on Facebook population maps.
Notes. The figure shows building detection from the algorithm. Red squares indicate houses detected.

Figure B.6. Cumulative distribution of plot area and annual production



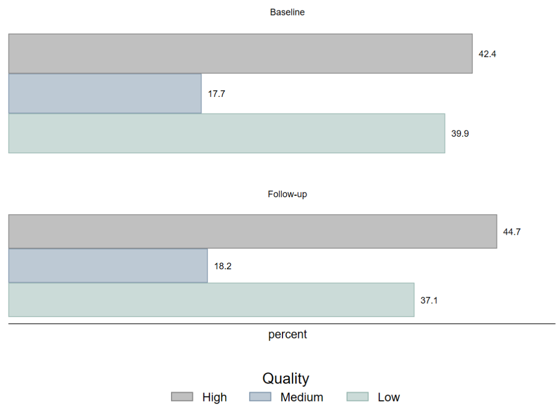
A. Cumulative distribution of plot area (in Ha)



B. Cumulative distribution of annual production (in Kg)

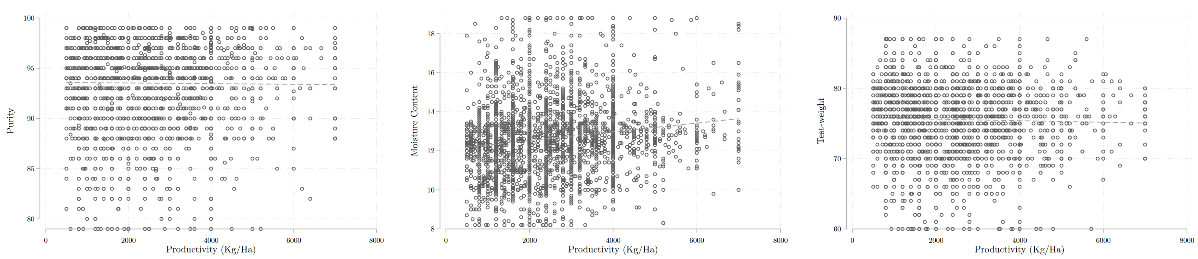
Source: Author's computations based on 2019/2020 wheat growers' survey.
Notes. This figure shows the cumulative distribution function (cdf) of plot size and wheat production. Panel A. shows the plot size (in Ha) cdf. Panel B. shows this year wheat production cdf. The plain curve is the observed cdf. The dashed curved represents the normal cdf.

Figure B.7. Quality distribution by survey round



Source: Author’s computations based on 2019/2020 wheat growers’ survey.
Notes. The figure shows at baseline and follow-up the distribution of wheat samples across quality grades based on objective assessment (i.e., laboratory test). The classification relies on three criteria: flour extraction rate (test-weight), moisture content, and purity content to obtain objective quality measures. Each of these dimensions was graded on a three-point scale based on the government’s official grading system. Then, the aggregate grade (i.e., low, medium, high) relies on the lowest factor approach.

Figure B.8. Relationship between quality attributes and productivity



A. Purity content   B. Moisture content   C. Test-weight

Source: Author’s computations based on 2019/2020 wheat growers’ survey.
Notes. The figure represents the relationship between each quality attribute (in %) and current year productivity (in kg/ha). Panel A. shows the relationship between purity content and productivity. Panel B. shows the relationship between moisture content and productivity. Panel C. shows the relationship between test weight and productivity.

C. Tables

Table C.1. Quality inspection format

Grade	High	Medium	Low
Purity content	[100; 92]	]92; 91]	]91; 88]
Moisture content			[13; 100]
Test-weight	[100; 77]	]77; 75]	]75; 73]

Notes. Results are expressed in percentage of the wheat sample analyzed. For moisture content, we use a two grade scale (i.e., low and high). For instance, a wheat sample with purity content of 94% is considered as high-quality in this dimension.

Table C.2. Balance tests: Market participation by survey round

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

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

Table C.3. Balance tests: Market participation by market type

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

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

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

	(1) Religious Day	(2) Rainy Week	(3) Rainy Day
Number of Farmers	181.45**	499.76***	449.63*
	(74.43)	(184.67)	(229.25)
Number of Traders	-23.76	-31.21**	-19.93
	(18.60)	(14.21)	(19.32)

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

D. Surveys

Table C.5. Price premium for different quality attributes, with heterogeneity by district agricultural specialization

Sample	(1) Not Specialized	(2) Specialized	(3) Not Specialized	(4) Specialized	(5) Not Specialized	(6) Specialized
High	0.02**	0.02***				
	(0.01)	(0.01)				
Medium	0.01**	0.00				
	(0.01)	(0.01)				
Quality Index			0.00	0.01*		
			(0.00)	(0.00)		
Impurity					0.15**	0.07
					(0.06)	(0.04)
Moisture					-0.00	0.03*
					(0.02)	(0.01)
Test-weight					-0.00	0.08
					(0.02)	(0.05)
Constant	2.42***	2.16***	2.43***	2.20***	1.76***	1.49***
	(0.09)	(0.13)	(0.09)	(0.08)	(0.34)	(0.42)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of *woredas*	22		22	8	22	8
N	2288	613	2245	611	2117	595

Notes. Price is expressed in logarithmic form. Low quality is considered as the value of reference. Quality index is the inverse covariance weighted summary index of quality attributes (i.e., purity, moisture , and test-weight) and increases with higher wheat quality. Purity, moisture and test-weight are expressed in logarithmic form. Specialized sample includes *woredas* for which the cereal with the highest share share of total cultivated land area is wheat. Not specialized sample corresponds to *woredas* for which wheat is not the cereal with the highest share share of total cultivated land area. Controls included: age of farmer i, gender of farmer i, yearly wheat production of farmer i, plot size of farmer i, travel time of farmer i to market j, type of wheat produced by farmer i, quantity sold by farmer i, and market day volume traded on market j. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Table C.6. Market price and market competition (first stage)

Endogenous variable:	(1) Competition
Religious day	-0.09**
	(0.04)
Pre-market week rainfall	-0.07*
	(0.04)
Market day rainfall	-0.11**
	(0.04)
F statistics	11.99
Overidentification p-value	0.06
Time FE	Yes
Market FE	Yes
N	3444

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

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

	(1)	(2)	(3)
Quality variable:	Purity	Moisture	Test-weight
Quality	0.15***	0.02	0.01
	(0.04)	(0.01)	(0.03)
Constant	1.92***	2.55***	2.57***
	(0.20)	(0.04)	(0.12)
Control	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Market FE	Yes	Yes	Yes
N	2714	2814	2689

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

Table C.8. Prediction (out-of-sample) accuracy for wheat price

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

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

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

Quality variable:	(1) Purity	(2) Moisture	(3) Test-weight
Quality	0.12***	0.04	-0.01
	(0.05)	(0.03)	(0.02)
District Market × Quality	0.10	-0.03	0.10*
	(0.11)	(0.03)	(0.05)
Constant	1.61***	2.60***	2.23***
	(0.42)	(0.05)	(0.20)
Control	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Market FE	Yes	Yes	Yes
N	2714	2814	2689

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

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

Quality variable:	(1) Purity	(2) Moisture	(3) Test-weight	(4) Purity	(5) Moisture	(6) Test-weight	(7) Purity	(8) Moisture	(9) Test-weight
Quality	0.17**	0.05**	-0.00	0.11***	0.05*	-0.01	0.03	-0.02	-0.01
	(0.07)	(0.02)	(0.03)	(0.07)	(0.03)	(0.02)	(0.08)	(0.02)	(0.02)
Relationship	0.16	0.11*	-0.21						
	(0.36)	(0.05)	(0.21)						
Relationship × Quality	-0.03	-0.04*	0.05						
	(0.08)	(0.02)	(0.05)						
Millers × Quality				0.07	-0.04	0.10**			
				(0.08)	(0.04)	(0.04)			
Cooperatives × Quality							0.18**	0.08**	0.08**
							(0.08)	(0.04)	(0.04)
Constant	1.78***	2.45***	2.56***	2.10***	2.49***	2.69***	1.93***	2.47***	2.49***
	(0.34)	(0.06)	(0.14)	(0.31)	(0.06)	(0.10)	(0.31)	(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	2714	2814	2689	2714	2814	2689	2714	2814	2689

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

Figure C.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 C.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.

1

Figure C.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)

1