Adverse selection in informal maize markets in Benin

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Abstract

We use panel data from Benin to investigate potential adverse selection in informal maize markets by matching farmers' maize sales with their knowledge, practices and perception of maize quality. Evidence suggests that rural households market a lower share of their grain stocks when they have better knowledge about quality issues and also invest in improving quality. This is most likely because there is no quality control and the price premium received for higher quality maize is not sufficient to incentivize improvements or investments in storage. We also find that farmers who sell a larger share of their maize stocks into markets might perceive that their storage practices impair quality. This behaviour is observed in the use of chemical protectant for which knowledge and information are limited in rural areas. Our findings highlight the need to develop long term grades and standards in African grain markets to ensure product differentiation and therefore develop rural markets through improved sale transactions. There is also need to provide rural sellers with better access to information about quality issues along with appropriate storage practices and technologies.

JEL-code : *C13, D13, O12, O33, O39*

Keywords: adverse selection, maize quality, storage practices, information.

1. Introduction

Improving smallholder farmers' market participation is important for enhancing food and income security in sub-Saharan Africa (SSA). Rural transactions remain, however, largely informal and prevent markets to vehicle opportunities for many rural sellers. Of a particular importance for well-functioning markets is a consistent supply of good quality grain (Hodges et al., 2011). Yet many food markets in SSA fail to provide consistently high quality. A lack of quality standards for grains creates additional market inefficiencies which prevent smallholder farmers from participating in cereal markets. As it is well known, adverse selection characterizes markets where products are not easily differentiated during transactions. To date, relatively little attention has been paid to the impact of these issues on rural sellers.

Recent evidence suggests that the inability of rural markets to differentiate products could explain farmers' lack of market participation. In Benin, for example, farmers who preserve maize from pest damage in order to sell during the hungry season cannot expect a price premium to rewards their efforts (Kadjo et al., 2016). This situation undoubtedly creates disincentives to farmers to invest in quality preservation. Otherwise, farmers who invest time and inputs to preserve quality may have a marginal utility for consuming good quality grain that market valuations are unlikely to match. Hoffman and Gatobu (2014) indicate that farmers place more value on their own grain compared with grain sourced from markets. The authors show that the difference in quality valuation between homegrown and market purchased maize might explain why many farmers do not participate in markets. They conclude that asymmetric information about unobservable food quality attributes may contribute to the prevalence of smallholder autarky in staple grains. But they do not test whether farmers' knowledge about quality inform their storage practices and subsequently their allocation of maize between consumption and sales in the household.

The objective of this paper is to investigate how farmers' knowledge, attitudes and perceptions (KAP) associated with maize quality affect their market participation during the post-harvest season. Our primary conjecture is that farmers are less likely to sell good quality maize into the markets because there is no quality control or sufficient price premium for quality. Quality attributes may be either observable such as presence of mold and insect damage, or unobservable such as the presence of Aflatoxin and residues of chemical (pesticide). We also hypothesize that farmers infer both observable and unobservable characteristics of maize quality from their KAP, and test this conjecture using a two-wave balanced panel of farm households located across Benin. These households were surveyed after the harvest seasons 2011/2012 and 2013/2014, with 309 households for our balanced sample. Specifically, we test the following five hypotheses:

1. Knowledge about the use of chemical protectant has no statistically significant effect on the amount of maize a farmer allocates to sales during the post-harvest season.
2. Perceptions about the potential health risks associated with chemical-contaminated maize have no statistically significant effect on the amount of maize a farmer allocates to sales during the post-harvest season.

3. The use of chemical protectant for storage has no statistically significant effect on the amount of maize a farmer allocates to sales during the post-harvest season.
4. Drying duration has no statistically significant effect on the amount of maize a farmer allocates to sales during the post-harvest season.
5. Perceptions about health risks associated with consuming moldy maize have no statistically significant effect on the amount of maize a farmer allocates to sales during the post-harvest season.

We do our best to ensure that the tested covariates are exogenous to farmers' market participation. We recognize, however, that we cannot make strong causal inferences in this context. Therefore, our results test at least the association between the tested variables and the quantity of maize that farmers sell during the post-harvest season, conditional of a set of covariates.

To date, there is limited understanding of how quality concerns affect market participation in informal food markets. In fact, the development literature emphasizes constraints such as transaction costs, assets and credit as key obstacles to smallholder households' participation in rural markets (Barrett, 2008; Boughton et al., 2011; De Janvry and Sadoulet, 2006; De Janvry et al., 1991; Jayne et al., 2010; Stephens and Barrett, 2011). Hoffman and Gantobu (2014) provide, to our knowledge, the first attempt to explain farmers' autarkic behavior by the asymmetric information they have for unobservable quality attributes. Maize quality can indeed be separated into two categories, namely unobservable and observable characteristics. Observable attributes of maize quality such as the presence of insect damage, mold, and color can easily be assessed by buyers and sellers during transactions. But buyers have limited information about unobservable attributes such as aflatoxin and chemical contamination. Sellers are also unable to evaluate maize quality for unobservable attributes. But they know more than buyers because they may infer unobservable characteristics from their storage practices. For instance, attributes such as chemical contamination from storage protectant applied to grain by farmers in order to kill insect pests are usually unobservable to buyers. But contamination from pesticide residues is likely to occur because farmers use uncertified chemical as storage protectant (Adegbola, 2010). Thus, chemical use provides two quality characteristics. That is the conventional, direct effect of pesticides used to control pests; and an indirect human health effect, operating through the potential exposure has on farmers' health (Antle and Pingali, 1994). Inadequate drying and storage under damp conditions also create the conditions for proliferation of mold and then *Aspergilus flavus* that lead to aflatoxin production and grain contamination (Hell et al., 2002; Johnny et al., 2011).

This paper extends the market failure argument to include quality issues that have received little attention up to now. Moreover, it provides new insights into how potential market failures for quality differentiation might result in adverse selection in rural markets, or the emergence of inefficient relational trading as a way of overcoming information asymmetries (Tadesse and Shively, 2013).

2. Conceptual framework

We build primarily upon Hoffman and Gantobu (2014) to investigate how farmers' efforts to improve grain quality affect their market behavior during the post-harvest season. We differentiate the harvest season, also called storage period, when farmers make most investments in time and inputs, from the post-harvest season when they sell or purchase maize (see figure 1). In addition, we follow Antle and Pingali (1994), Liu and Huang (2013) to account for the fact that some storage practices such as chemical protectant (pesticide) may have both positive and negative effects on maize quality.

Risk averse households with characteristics ***(Z)*** maximize their utility during the post-harvest season from consuming only one staple food $[q_h^c(\bar{a})]$ sourced from their own production or purchased from market $[q_p^c(\bar{b})]$; where $(\bar{a})$ and $(\bar{b})$ represent both vectors of good maize attributes that can be either observable (o) or unobservable (u), $\overline{a} = [\overline{o}, \overline{u}]$. The households can also obtain utility from consuming non-food good *(x).* The households' problem is stated as follows:

$$Max\ U(q_h^c(\bar{a}) + q_p^c(\bar{b}),\ x;\ \boldsymbol{Z}) \tag{1}$$

The quantity of maize is increasing in attributes. Attributes are, in turn, increasing in a set of knowledge, attitudes and perceptions. Attitudes comprise the use of storage inputs (n), time *(l)* allocated to some practices such as drying and knowledge about health risk associated with poor quality grain. Farmers adopt storage practices to achieve good quality attributes $(\overline{a})$. But quality attributes are modified if farmers perceive a risk of chemical use. Quality attribute for unobservable characteristic such as chemical contamination can be written as in equation (2)

$$a(u) \;= (\,1 + m(I)) * \overline{a}(\overline{u}) \tag{2}$$

Where $m(I)$ is a parameter representing the effective management of chemical use and I ($\equiv \underline{u}$) health impairment or contamination risk. If farmers (believe to) adopt an effective management of chemical use, $m(I) = 0$, and they may achieve good unobservable quality ($\overline{u}$). Otherwise, $m(I)$ is negative and decreasing so that farmers can only achieve bad quality ($\underline{u}$).

Let us first assume a situation where farmers achieve good grain quality *($\bar{a}$)* for both observable and unobservable attributes. They allocate their stock (Q_h) to consumption [$q_h^c(\bar{a})$] or sales [$q_h^m(\bar{a})$] as shown in equation (3)

$$Q_h \;= q_h^c(\bar{a}) + \; q_h^m(\bar{a}) \tag{3}$$

Equation (4) is the liquidity balance:

$$p_h^m(\bar{a}).\, q_h^m(\bar{a}) + \; p.q - \; p_n \; n\left(\overline{a}^E\right) - wl(\bar{a}^E) \;\; \geq \;\; p_p^c(b).\, q_p^c(b) \tag{4}$$

In equation (4) the parameter[$p_h^m(\bar{a})$] represents the price farmers receive for selling maize during the post-harvest season, whereas [$p_p^c\left(\overline{b}\right)$] is the price they pay for purchasing maize from markets. We use the parameters *p* and *q* for the price and the quantity of sales maize during the harvest season respectively. The parameters p_n and *w* respectively denote the price for chemical protectant for storage and the labor wage.[1] Farmers invest in inputs and labor during the harvest season or in the early post-harvest season because they expect certain maize qualities. The parameter $\overline{a}^E$ represents the vector of expected quality for observable and unobservable attributes that farmers want to achieve during the post-harvest season.

We consider an alternative situation where farmers want to decide how to choose the amount of maize to sell maize that could have been allocated to consumption[2]. Thus, grain sales become an endogenous variable.

1 The price for the non-food good is normalized to unity.
2 The fact that many farmers buy back (40% in our sample) maize shows that they do not secure consumption first.

If the households are indifferent to quality, then simple first-order conditions with respect to the endogenous variables $[q_h^m(\bar{a})]$, $[\ q_p^c(\bar{b})]$, and (x) lead to the standard results of the ratio of marginal utility equates to the price ratio.

Specifically, the first order condition with respect to the amount of maize sold is as follows:

$$\frac{\partial \mathcal{L}}{\partial q_h^m} \equiv -U_{q_h^m} + \lambda . p_h^m(\bar{a}) \qquad = 0 \tag{5}$$

The parameter λ is the Lagrange multiplier for equation 4. The parameter $(U_{q_h^m})$ is the marginal utility with respect to the amount of maize sold.

But if the households are concerned about good maize quality, we can extend the maximization problem to the endogenous $(\bar{\mathrm{a}})$**.** The new marginal utility for consuming maize with a given quality attribute will be increasing more than before owing to the chain of the link effect between quality and quantity. In other words, marginal utility with respect to maize quality increases because marginal utility is increasing in maize quantity, and maize quantity is, in turn, increasing in maize quality

The first order condition with respect to maize quality is such that[3]:

$$\frac{\partial \mathcal{L}}{\partial \bar{a}} \equiv U_{q_h^m} * \frac{\partial q_h^m}{\partial \bar{a}} + \lambda \left[p_h^m(\bar{a}) . \left(\frac{\partial q_h^m}{\partial \bar{a}} \right) + q_h^m(\bar{a}) . \frac{\partial p}{\partial \bar{a}} - p_n . \frac{\partial n}{\partial \bar{a}} - w . \frac{\partial l}{\partial \bar{a}} \right] = 0 \tag{6}$$

When we account for equation (5) into equation (6), we can derive equation (7) as follows:

$$\frac{\partial \mathcal{L}}{\partial \bar{a}} \equiv \lambda . p_h^m(\bar{a}) * \frac{\partial q_h^m}{\partial \bar{a}} + \lambda \left[p_h^m(\bar{a}) . \left(\frac{\partial q_h^m}{\partial \bar{a}} \right) + q_h^m(\bar{a}) . \frac{\partial p}{\partial \bar{a}} - p_n . \frac{\partial n}{\partial \bar{a}} - w . \frac{\partial l}{\partial \bar{a}} \right] = 0 \tag{7}$$

We can also rewrite equation (7) to obtain the equilibrium in equation (8)

$$2\ p_h^m(\bar{a}) * \frac{\partial q_h^m}{\partial \bar{a}} + q_h^m(\bar{a}) . \frac{\partial p}{\partial \bar{a}} = p_n . \frac{\partial n}{\partial \bar{a}} + w . \frac{\partial l}{\partial \bar{a}} \tag{8}$$

Equation (8) indicates that the marginal cost of the efforts to obtain good quality is equal to the sum of (i) the value gain from the additional amount of maize due to the quality improvement

3we assume that $a^E \equiv$ a in the post-harvest season to suggest that the household achieves the expected quality.

and (ii) the price premium for quality in the market. This equilibrium is intuitive and is a standard equilibrium. The value gain from the additional amount of maize can be achieved as long as farmers decide to sell this additional amount obtained from quality improvement into the markets. By contrast, price premium depends on market characteristics. Thus, if there is no price premium, efforts are costlier than what the market will pay for. In such a situation it is no longer optimal for rural households to allocate maize with good attribute $\overline{(a)}$ to markets.

Bu we obtain different implications from the equation (8), if farmers believe that the use of chemical might be harmful. This corresponds to a situation where *m(I)* is different from zero. The use of chemical during the harvest season will depend on new expected quality attributes where only unobservable characteristics are modified. In equation (9), we write chemical use under a new form (n_f) that accounts for contamination risk as a function of the initial chemical use without risk

$$n_f \ (u^E) = \big(1 + n(I)\big)n(\overline{u}) \tag{9}$$

Because $\frac{\partial n_f}{\partial u^E} < \frac{\partial n}{\partial u^E}$ the marginal cost of the efforts to obtain good quality when farmers perceive a contamination risk is lower than it is without risk. This implies that farmers who perceive the risk of chemical use are likely to sell more grain into markets than other farmers do.

3. Empirical estimation

Empirical model

The literature on market participation in food markets in SSA indicates that a farmer's decision to participate in a market and the decision about how much grain to trade can be made simultaneous or sequentially. A simultaneous model of market participation assumes that the two decisions are generated by the same process while a sequential decision model recognizes that the decisions might be independently driven by different factors (Bellmare and Barrett, 2006; Burke et al., 2015). Our theoretical model suggests that farmers would not pre-commit to selling high-quantity maize without assessing how the market values quality as in equation (8). It is, therefore, reasonable to assume a sequential decision-making process in which farmers first decide to participate in the market and then choose an amount to sell. We test, however, the alternative hypothesis of a simultaneous decision using a likelihood ratio test.

Equation (10) represents the first stage regression of a double hurdle corresponding to the probability that a farmer *(i)* sells maize during the post-harvest season *(t)*[4]**.**

$$P_{it} = \Phi(K_{it},\ \boldsymbol{A_{it}}, \boldsymbol{V_{it}}, \boldsymbol{X_{it}}, u_{it}) \qquad (10)$$

The parameter K_{it} represents farmers' knowledge about maize quality issues. The vector $\boldsymbol{A}$ denotes farmers' attitudes that correspond to storage practices. The vector $\boldsymbol{V}$ represents farmers' perception about health risk from consuming poor maize quality. The Vector $\boldsymbol{X_{it}}$ accounts for control variables from the theoretical framework including transaction costs, household assets, liquidity constraints and farmers' characteristics. The parameter u_{it} corresponds to the error term.

Equation (11) defines the hurdle (2) of our regression. It treats the amount of maize sold into markets as conditional on the first stage.

$$S_{it} = \mathrm{g}(K_{it},\ \boldsymbol{A_{it}}, \boldsymbol{Pe_{it}}, \boldsymbol{X_{it}}, \in_{it}) \qquad (11)$$

The parameter (S_{it}) is the amount of maize that is sold into markets during the post-harvest season. The other parameters in equation (11) are defined as before. We test our hypotheses through the estimate and the statistical significance of the coefficient on the covariates of interest. The parameter ($\in_{it}$) denotes the error term in equation (11).

Identification strategy

We first address the issues of simultaneity and reverse causality between the tested variable and the dependent variables. There is no concern of potential endogeneity caused by simultaneity bias since the tested covariates are predetermined to the decision of market participation and to the quantity of maize sold into markets. In fact, to preserve maize quality farmers adopt a set of

[4] Although one could believe that farmers' net food status might affect their quality valuation because of income effect, an ordered probit model that ranks the three categories of net food status (net buyers, autarkic, net sellers) was not appropriate. Indeed, the cut points for the ordered probit are not statistically significant. Results are not presented here for the sake of brevity but are available upon request.

practices during the storage period or in the early stage of the post-harvest season. Reverse causality should not also be an issue for identical reasons.

Endogeneity from omitted variable bias could be a serious issue in this application. One might argue that some storage practices during the harvest season could determine their market participation later in the post-harvest season. We deal with this issue by including in the vectors ***X*** covariates that could affect both farmers' storage practices and market participation. We include variables such as farmers' storage goal during the harvest season, the proportion of maize produced that is sold during the harvest period. We also account for covariates that evaluate how easy a farmer may have access to information about storage practices and markets. Thus, we control for the presence in the village of an extension agent and an input dealer. We capture transaction costs through distance from the main markets. Likewise, we introduce farmers' assets.

Another possible endogeneity issue may arise from chemical use that might not be random. Studies and field observations reveal that many farmers face constraints to accessing appropriate storage chemical technology. Recommended chemical protectants such as Sophagrain and Actellic were promoted by projects that facilitated credit access and supply of these protectants (Adegbola, 2010). Unfortunately, the implementation of these projects did not address other long-term constraints to adoption of these new technologies such as high costs, and availability of products (Adegbola, 2010). As a result, access to appropriate chemical protectant is limited, and farmers are still using traditional conservation measures or farm pesticides and other chemical they believe appropriate to deal with pest damage (Adegbola, 2010; Hell et al., 2000). Therefore, we could assume that chemical use is random as farmers can have access to farm pesticide from any available input dealer in the village or in the markets (Ricker-Gilbert and Jones, 2015). Nevertheless, we follow a control function approach and test the endogeneity of chemical expenditure. We use the number of years the household head has belonged to an association or a group in the village as the instrumental variable. This instrument measures how easy a farmer may have access to chemical protectant through community networks. But we do not believe that the instrument could have a direct effect farmers' sale transaction. We do not find that chemical expenditure is endogenous in the DH hurdle model (Appendix 1). Therefore, we believe that controlling for covariates that account for market participation and access to storage protectant may take care of other possible endogeneity of chemical use caused by omitted variable bias.

Moreover, the use of panel data in this context allows us to address the issue of unobserved heterogeneity that could create additional endogeneity issue. Since the use of FE could result in inconsistent parameters when applied to non-linear models due to the incidental parameter problem (Wooldridge, 2010), we use the Mundlack-Chamberlin (MC) device to deal with unobserved heterogeneity, denoted as c_i in the non-linear model estimated in equation (10) (Mundlak 1978, Chamberlain 1984). Under the MC-device, the assumption of independence between covariates and unobserved heterogeneity (c_i) can be relaxed by modeling (c_i) as follows

$$c_i = \varphi_{ij} \quad + \overline{\boldsymbol{W}}_{\boldsymbol{i}}\xi + e_{it} \tag{12}$$

The MC device assumes that $e_{it} \mid \bar{X}_{it} \sim Normal(0,\ \sigma_i^2)$ where $\overline{\boldsymbol{W}}$ is the household time average of all time-varying covariate in equation (10). This specification provides estimates that analogous to household FE estimation (Wooldridge, 2010). The MC-device remains also appropriate for estimating equation (11) for hurdle 2 because some tested covariates are time invariant. We apply the MC-device to other regressions for identical reasons.

Selection bias

Nearly 20% of farmers do not participate in sale transactions during the post-harvest (post-harvest period). These zero volumes of transaction represent the households' optimal decision, and are thus observed data, but not missing data. They indicate that some farmers selling (buying) have their reservation value above (below) market prices. But the transaction prices for farmers not selling during the post-harvest seasons are missing. For these farmers, we use the mean price for farmers who sell maize in a given village as their opportunity cost.

4. Data

Data collection

Data come from a random survey conducted in 6 of the 12 departments in Benin. Districts were randomly chosen within a given department. Counties called "Sous-prefecture" were also randomly selected in the district, followed by a random choice of villages. In the first stage, survey enumerators conducted a census of maize farmers in each selected village to identify the pool of households. In the second stage, 30 farmers were randomly chosen among these households.

The survey covered a consumption cycle for each farmer (see figure 1) for the 2 waves of data collection, namely 2011/2012 and 2013/2014 harvest seasons. The first wave data cover 360 households, but only 310 of these farmers were successfully interviewed during the second wave or have data complete set of information. We also drop one observation for a farmer whose size (Ha) is more 51 time the average size and cannot be considered as a smallholder farmer. We end up with a balanced sample of 309 farmers and 618 individual observations.

Descriptive statistics

Foods status

We record a large proportion of maize sellers. Maize sellers amount to 432 farmers (70% of the sample). We find only 186 farmers who do not sell maize (30% of the sample). The pattern of market participation remains almost unchanged over the two years. Indeed, 83% of farmers who sold maize in year one sold again in year two. Similarly, 67% of farmers who did not sell maize in the first wave, continued to withhold grain from the market in the second wave. This pattern is consistent with the idea that most farmers probably did not change their storage practices over the two years.

[Table 1. Here]

Knowledge: how to use chemical protectant and the consequence of its misuse

Most farmers (55%) report using the grain odor to identify chemically contaminated grain, whereas indicate 36% of the sample do not know how to detect this contamination. To measure knowledge about quality from chemical use, we use the cumulative number years a farmer has been trained or informed about how to use chemical protectant.

Attitude: Use of chemical protectant

We use expenditure on storage protectant, measured in real value (2011 in the base year), as the variable for chemical use. Table 1 shows that 25 % of farmers apply chemical protectant from whom only 17% use certified chemicals such as attelic or sophagrain. A large proportion of farmers applies either farm pesticide or unknown chemical to protect their stock against pest damage.

Attitudes: Drying duration

Maize drying is a critical step in reducing the moisture content and preventing fungal growth and aflatoxin production. But few farmers (only 9 in our sample) are aware of aflatoxin contamination.

We use the drying duration for maize (in days) to measure the effort that farmers devote to this storage practice. Specifically, we measure how long farmers dry maize cob or shelled maize. We then compute a unique measure representing the total number of days that farmers devote to drying practice. In the study area, maize is more often dried on the cob compared to the shelled one (Table 2).

[Table 2. Here]

Perception: Do farmers know what is good or bad maize quality?

We present farmers with two situations of bad maize quality. The first is a chemical contaminated maize and the second is maize with more than > 30% mold content. We then ask them to indicate whether they will eat these quality attributes or allocate them to other use other than their own consumption. We assume that farmers who eat all maize of a given bad quality attribute consider it safe for consumption. Thus, farmers who consider bad quality as unsafe for consumption have a good information system about quality issues and can distinguish good quality maize from a bad one. We categorize them as farmers who perceive a quality risk. But farmers who consider bad quality as safe for consumption have a bad information system about quality and are not systematically able to differentiate different maize qualities.

In table 1 we find only 40% of farmers who are aware of the risk of chemical contamination. We record 85% of farmers aware of the risk of mold contamination. The difference between these two perceptions could be explained by the fact that farmers report more cases of mold intoxication (20 farmers) than they do for chemical intoxication (7 farmers). In addition, chemical contamination is less a visible risk compared to the presence of mold.

[Table 3. Here]

Table 3 presents unconditional mean differences in storage practices between farmers with different perceptions of contamination risk. Table 3 shows that farmers aware of the risk of chemical contamination use less certified chemical. They elicit a longer latency period after applying chemical and they dry maize longer. We also observe the same behavior for farmers aware of the risk from mold.

Attrition bias

Attrition bias caused by farmers leaving the sample is a major issue to address. Of 360 of the first wave of data collection, only 314 were successfully interviewed during the second round and 309 had a full set of information available. Thus, we rely on 309 farmers as the balanced panel for our analysis. Unfortunately, there is no regression-based test for attrition bias when FE and CRE are used with two time periods only. The regression models in our analysis control for attrition bias to the extent that attrition is related to the observed covariates and/or time-constant, unobserved effects (Mason and Smale, 2013; Mason and Ricker-Gilbert, 2013).

5. Econometrics results

Table 4 shows the Tobit estimation combined with M-C device to evaluate how farmers' knowledge, practices, and perception affect the amount of maize sold in markets. Results in column 1 show the parsimonious regression of the main covariates from the theoretical framework. We find that chemical expenditure has a negative effect on the quantity sold into markets. The estimate for the tested variable, chemical expenditure, is statistically significant with p-value < 0.01. Similarly, other tested variables such as knowledge and awareness of the risk of chemical contamination lead farmers to sell less during the post-harvest season. But these variables are not statistically significant. Drying duration, on the contrary, is positive and statistically significant in column (1), but not robust when we control for more covariates in column 2. The estimates for chemical expenditure remains, however, robust. Results in column 2 indicate that a 1,000 F CFA (about $ 2 US) increases in expenditure for chemical protectant decreases the average amount stored by 41 kg, with p-value =0.01. In column 3, we introduce an interaction term between farmers’ risk perception and storage practices. We find that farmers who spend on chemical protectant while unaware of the risk of contamination sell less into the markets. The average quantity sold is reduced by 46 Kg for a 1,000 F CFA spent on chemical. But farmers who perceive the risk of chemical use sell a little more into markets when they use chemical protectant. The average sale is only reduced to 32 Kg for these farmers. In effect, the variables chemical cost and the interaction term (chemical use x chemical risk) are jointly statically significant with p-value < 0.01. These results make sense since farmers unaware of the risk of chemical contamination associate the use of storage protectant with less pest damage, but not with contamination risk. Since our analysis rests on the premise of an insufficient price premium for good quality maize, this result is also consistent with the theoretical framework in situations where farmers consider the effective management of chemical use *(m(I)*) to be equal to zero. The more farmers spend on chemical the less they sell into markets. But when farmers perceive the risk of chemical use the theoretical framework corresponds to situations where the effective management of chemical might be different from zero. Indeed, very few farmers who are aware of contamination risk use known certified protectant compared to other farmers (See table 3). Because the management of chemical use is ineffective, the marginal cost of the effort to improve quality is lower under perceived risky situations than it is in opposite situations. Therefore, farmers may want to sell more into the markets. Knowledge about chemical and drying practices also have a negative effect on the average amount sold, but their estimates are not statistically significant.

[Table 4. Here]

Table 5 shows the DH model of the effects of farmers' knowledge attitudes and perceptions on the quantity of maize sold during the post-harvest period. The coefficients in column 1 & 2 correspond to the DH without an interaction term between storage practices and risk perception. The estimates in column 1 are the conditional APEs. Results in column 1 indicate that a 1,000 F CFA ($ 2 US) increase in chemical expenditure increases farmers’ average probability to selling maize in markets by 1 percentage point, with p-value =0.10. Likewise, an increase in one day of drying practices increases the average probability of market participation by 0.2 percentage point. The positive effects of chemical expenditure and drying practices on market decision could be explained by the fact that farmers want to compensate for the cost of their efforts. By contrast, farmers’ knowledge and perception have a negative effect on their probability to participate in markets. But only the tested variable, knowledge, is statistically significant with p-value =0.06. The estimate suggests that an additional year of knowledge reduces farmers’ average probability of market participation by 5 percentage point. In column 2 of table 5, we estimate the second hurdle of the effect of the tested covariates on the quantity sold conditional on the decision to sell maize. Results show that storage practices have a negative effect on the quantity of maize sold into markets. But only the estimate for expenditure on protectant is statistically significant, with p-value < 0.01. We find that a 1,000 F CFA ($ 2 US) increase in expenditure for chemical protectant reduces the average quantity sold by 35 Kg.

Columns 3 & 4 of table 5 are the results of a DH model accounting for an interaction term between storage practices and farmers' risk perception from some storage practices. As before, the results in column 3 (hurdle 1) suggest that farmers who spend on chemical protectant with unperceived risk from chemical use are most likely to participate in cereal markets. The APE increases by 3 percentage point for a 1,000 F CFA spent on storage protectant. Farmers who dry maize with unperceived risk about mold are less likely to sell into the market. But the estimate is not statically significant. Other tested covariates such as knowledge and perception are negative but also not statistically significant.

[Table 5. Here]

In column 4 (hurdle 2) of table 5, we account for the interaction term to explain the quantity of maize sold conditional on the decision to sell (Hurdle 1). We find that farmers who spend on storage protectant unaware of the risk sell less maize into the markets. An increase of 1 000 F CFA on chemical reduces the average quantity sold by 44 Kg. But sales are reduced to only 14 Kg for every 1,000 F CFA ($ 2 US) spent on chemical when farmers perceive the risk of chemical contamination. This result suggests farmers better aware of the risk from chemical use sell more into the markets. We believe that our explanations provided for the Tobit results are also applicable in the case of the DH estimation. That is the cost of the efforts for improving quality reduces because the ineffective management of chemical use may cause contamination risks, unobservable to buyers. However, our results in column 4 of the double hurdle imply that the reduction of the cost of the efforts is substantial. The DH estimation provides, indeed, a better fit for our sample compared to the Tobit estimation. Another covariate of interest is drying duration that has a negative, but not statically significant effect on the quantity of maize sold into markets.

6. Conclusion

In this paper, we investigate potential adverse selection in informal food market using evidence from maize in Benin. Adverse selection might result from the inability of markets to differentiate maize quality due to insufficient price premium or inexistence of quality control systems. We rely on a theoretical framework to suggest that in the absence of price premium for good quality maize, rural households sell less into the markets if they invest time and inputs in quality improvement and do not perceive risk from their storage practices.

Our findings indicate that there could be adverse selection in informal maize markets. Smallholder households who improve maize quality through drying might sell less into the markets (Hoffman and Gantobu, 2014). Our results also reveal that an increase in expenditure for chemical protectant is associated with a higher probability for farmers to participate in markets most likely because they want to compensate for the cost. But farmers who use chemical protectant sell less stored maize when they are unaware of the risk of chemical use. This means that the benefit from better quality maize, such as grain without pest damage, accrues to their own use since the markets do not value good quality grain even in periods of food scarcity (Kadjo et al., 2016). By contrast, farmers who perceive the risk of chemical use sell more maize into the markets.

This study highlights the fact that informal food markets create more than adverse selection. This adverse selection impedes farmers' market participation and could result in health risk for maize consumers. Nevertheless, information about maize quality and good storage practices remains largely imperfect to the extent that smallholder sellers might also be trapped in health risk because of their poor assessment of what is good quality maize. This study underscores the need to develop long term grades and standards in African markets to ensure product differentiation and develop cereal markets. There is also need to provide rural sellers with better access to information about quality issues along with appropriate storage practices and technologies.

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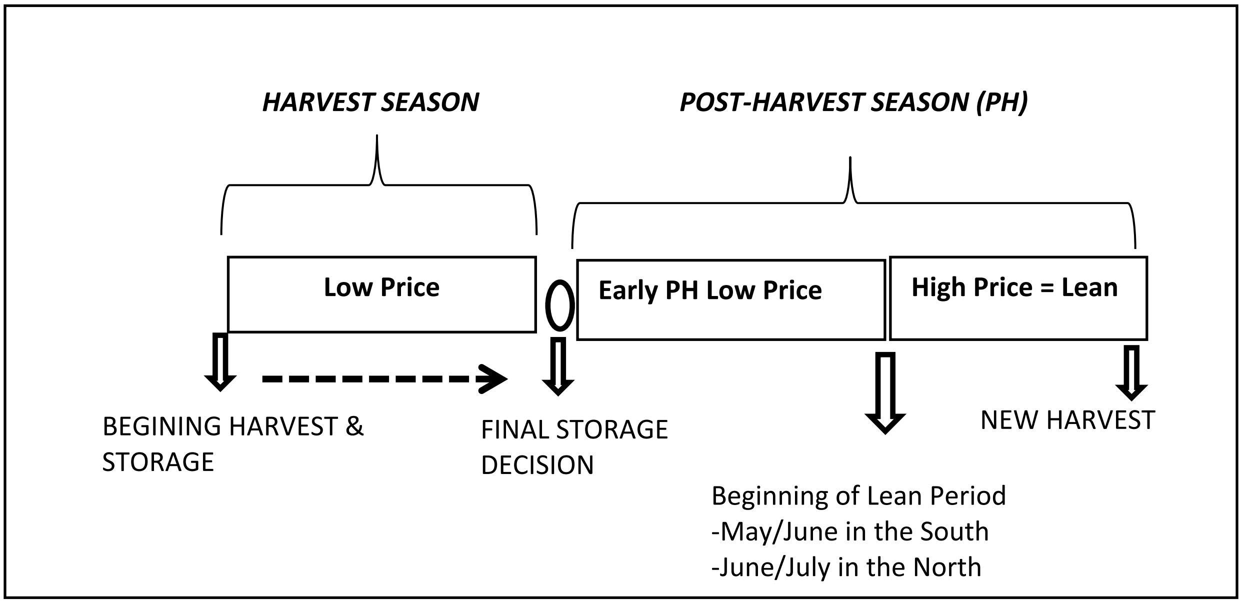

Figure 1. Maize Consumption Cycle

Table 1. Descriptive statistic for discrete covariates (in %)

	Pooled	2011	2013
=1 if HH head is an autarkic farmer	16.6	15.2	18.1
=1 if HH head is a maize seller	69.9	69.6	70.2
=1 if HH head uses chemical	24.9	23.6	26.2
=1 if HH head perceives risk of chemical use	44.0	44.0	44.0
=1 if HH head perceives risk of mold	85.4	85.4	85.4
=1 if storage goal includes sales	65.0	66.3	63.8
=1 is HH Head is educated	36.6	36.6	36.6
=1 if gender is Male	90.6	90.6	90.6
=1 if input dealers lives in the village	13.3	17.2	9.4
=1 if extension agent lives the village	41.7	57.6	25.9

Table 2. Descriptive statistics for continuous covariates

	Pooled sample		2011		2013	
	mean	p50	mean	p50	mean	p50
% of maize stock sold	0.4	0.42	0.4	0.4	0.4	0.4
Quantity sold (Kg)	1,610	400	1,504	363	1,717	400
chemic cost (1,000 F)	1.3	0.0	1.1	0.0	1.5	0.0
Knowledge (# Years)	0.6	0.0	0.5	0.0	0.8	0.0
Dry shelled Maize (# days)	0.6	0.0	0.6	0.0	0.6	0.0
Dry Maize cobs (# days)	1.7	0.0	1.7	0.0	1.7	0.0
Drying duration (# days)	2.3	0.0	2.3	0.0	2.3	0.0
Post-hav price (F cfa/Kg)	143.6	137.9	136.4	124.9	150.9	140.7
Maize stock (Kg)	2,556.1	1,107.5	2,342.8	1080.0	2769.3	1150.0
Sale share at harvest (%)	0.1	0.0	0.1	0.0	0.1	0.0
Farm size (Ha)	4.4	3.0	3.7	2.8	5.2	3.5
Saving (1,000 F CFA)	153.6	24.1	87.5	0.0	219.7	69.6
Age	43.7	42.0	42.7	40.0	44.8	42.0
Household size	10.7	9.0	10.6	9.0	10.9	10.0
Distance (Km)	5.9	6.2	5.9	6.2	5.9	6.2
Year in the association (#)	3.6	1.0	3.3	1.0	3.9	0.0

Table 3. Mean difference between farmers' perception for knowledge and storage practices[a]

	Chemical risk			Mold risk		
	Unaware	Aware	P-val.	Unaware	Aware	P-val.
Knowledge (Years)	0.7	0.4	0.13	0.8	0.6	0.43
=1 if HH uses Chemical (%)	3.0	3.0	0.38	3.0	3.0	0.59
=1 if HH uses certified chemic (%)	6.0**	2.0**	0.02	3.0	5.0	0.31
Chemical cost (1,000 F CFA)	2.1	1.2	0.21	0.9	1.8**	0.06
Latency period for chemical (# Days)	27.0***	43.7***	0.01	21.6***	36.6***	0.01
Dry. shelled Maize (# Days)	0.3	0.9	0.14	0.1	0.6**	0.03
Drying Maize cob (# Days)	0.7	1.7**	0.03	0.3	1.3***	0.00
Drying duration (# Days)	0.9	2.6**	0.02	0.5	1.9***	0.00
=1 if storage goal is consumption.	0.4	0.3	0.12	0.3	0.4	0.73

[a] t-test for continuous variables, and Chi2 for discrete variables; *** p<0.01, ** p<0.05, * p<0.10

Table 4. Factors that affects the amount of maize sold during the post-harvest period (Tobit-MC estimation)

	Column 1		Column 2		Column 3	
	Parsimonious		Full (1)		Full (2)	
VARIABLES	APE	P>z	APE	P>z	APE	P>z
chemical cost (1,000 F cfa)	-36.8***	(0.00)	-41.4***	(0.00)	-45.9***	(0.00)
Knowledge (# Year)	-12.3	(0.88)	-6.5	(0.93)	-20.7	(0.80)
=1 if risk of chemical cont.	-45.2	(0.60)	1.6	(0.98)	-5.6	(0.94)
Drying duration (# days)	2.0*	(0.09)	-0.4	(0.69)	-13.9	(0.38)
=1 if risk of mold cont	-63.1	(0.51)	-31.7	(0.73)	-34.4	(0.72)
Chemical cost x Risk C.					13.3	(0.39)
Drying x Risk of Mold					13.6	(0.39)
Post-harv. Price (F cfa/Kg)	2.3*	(0.06)	1.6*	(0.06)	1.5*	(0.07)
Maize stock (Kg)	0.5***	(0.00)	0.5***	(0.00)	0.5***	(0.00)
=1 if storage goal includes sales			740.9***	(0.00)	743.6***	(0.00)
% of maize sold at harv.			191.0	(0.24)	189.4	(0.24)
Total Farm size (Ha)			8.9	(0.30)	9.2	(0.27)
Savings (x 1,000 F CFA)			-0.2	(0.36)	-0.2	(0.37)
Age			10.2	(0.38)	9.2	(0.42)
Age square			-0.1	(0.47)	-0.1	(0.51)
=1 if gender is male			35.0	(0.64)	29.5	(0.69)
=1 if HH attended school			-69.1	(0.33)	-66.1	(0.35)
Household size			-40.9***	(0.01)	-40.7***	(0.01)
distance from market (Km)			7.9	(0.23)	8.4	(0.21)
=1 if input dealer in vil.			304.3	(0.18)	297.6	(0.19)
=1 if extension agent in vil			25.6	(0.65)	28.8	(0.61)
Department dummies		YES		YES		YES
Time average		YES		YES		YES
Constant	-1548***	(0.00)	-2179***	(0.00)	-2128***	(0.00)
Observations	618		618			618
Pseudo R2	0.15		0.17			0.17

*** p<0.01, ** p<0.05, * p<0.1

Table 5. Double hurdle of factors that affect the amount of maize sold during the post-harvest period

	Col 1: Hurdle 1		Col 2: Hurdle 2		Col 3: Hurdle 1		Col 4: Hurdle 2	
	Probit-MC		Trunc-Normal-MC		Probit-MC		Trunc-Normal-MC	
VARIABLES	APE	P>z	APE	P>z	APE	P>z	APE	P>z
chemical cost (1,000 F cfa)	0.01*	(0.10)	-34.96***	(0.00)	0.03***	(0.01)	-44.36***	(0.00)
Knowledge (# Years)	-0.05	(0.06)	55.59	(0.63)	-0.04	(0.16)	17.06	(0.89)
=1 if risk of chemical cont.	-2E-03	(0.96)	-229.07	(0.11)	-2E-04	(1.00)	-226.55	(0.11)
Drying duration (# days)	2E-03**	(0.04)	-0.57	(0.67)	-1E-03	(0.84)	-56.29	(0.30)
=1 if risk of mold cont	-0.01	(0.76)	195.36	(0.15)	-0.01	(0.65)	193.50	(0.17)
Chemical cost x Risk of C.					-0.03*	(0.08)	29.91	(0.03)
Drying x Risk of mold					0.00	(0.60)	56.04	(0.30)
Post-harv. Price (F cfa/Kg)	8E-04**	(0.02)	2.87	(0.12)	8E-04	(0.02)	2.47	(0.19)
Maize stock (Kg)	3E-05***	(0.01)	0.52***	(0.00)	3E-05***	(0.01)	0.52***	(0.00)
=1 if goal includes sales	0.48***	(0.00)	-295.65	(0.16)	0.50	(0.00)	-274.03	(0.19)
% of maize sold at harv.	-0.18*	(0.06)	203.94	(0.58)	-0.18*	(0.07)	181.85	(0.62)
Total Farm size (Ha)	0.01	(0.18)	11.89	(0.21)	0.01	(0.19)	11.97	(0.20)
Savings (x 1,000 F CFA)	0.00	(0.34)	-0.16	(0.22)	0.00	(0.32)	-0.12	(0.37)
Age	4E-04	(0.93)	-0.28	(0.99)	9E-04	(0.85)	-3.51	(0.85)
Age square	-6E-06	(0.89)	0.02	(0.90)	-1E-05	(0.81)	0.05	(0.78)
=1 if gender is Male	-0.02	(0.63)	168.71	(0.15)	-0.01	(0.72)	166.76	(0.15)
=1 if HH attended school	0.02	(0.49)	-190.25*	(0.08)	0.02	(0.51)	-183.22*	(0.09)
Household size	-0.01	(0.04)	-33.08	(0.17)	-0.01**	(0.03)	-32.41	(0.18)
distance from market (Km)	0.01*	(0.08)	-6.50	(0.56)	0.01	(0.05)	-5.07	(0.65)
=1 if input dealer in vil.	0.15***	(0.01)	25.44	(0.92)	0.15**	(0.01)	20.89	(0.93)
=1 if extension agent in vil	0.06*	(0.07)	-131.58	(0.29)	0.06*	(0.07)	-118.15	(0.34)
Department dummies		YES		YES		YES		YES
Time average		YES		YES		YES		YES
Constant	-2.02*	(0.09)	-1463.92	(0.12)	-2.19*	(0.07)	-1370.16	(0.13)
Observations		618		432		618		432
Pseudo R2		0.65				0.65		

*** p<0.01, ** p<0.05, * p<0.1

Appendix 1. Control function approach

	Reduced form		Double Hurdle			
	Dep var: Chemical cost		=1 if farmer sells maize		Quantity sold (Kg)	
	Tobit-CRE		Probit-CRE		Truncreg -CRE	
VARIABLES	APE	P>z	Marg	P>z	Marg	P>z
Instrument: # Years in association	0.06***	(0.01)				
Residual			**0.04**	**(0.73)**	**17.67**	**(0.67)**
chemical cost (1,000 F CFA)			**0.05**	**(0.60)**	**-11.94**	**(0.64)**
Knowledge (# Years)	0.40	(0.22)	-0.12	(0.84)	-730.53***	(0.01)
=1 if risk of chemical contamination	0.14	(0.59)	-0.39	(0.26)	273.30**	(0.05)
Drying duration (# days)	0.01**	(0.03)	0.04	(0.30)	-3.56	(0.25)
=1 if risk of mold contamination	-0.05	(0.87)	0.29	(0.60)	1210.83**	(0.10)
Post-harvest Price (F CFA/Kg)	0.01	(0.24)	0.01**	(0.02)	1.10	(0.68)
Maize stock (Kg)	8E-05	(0.18)	3E-04	(0.14)	0.89***	(0.00)
=1 if storage goal includes sales	-0.58	(0.30)	4.28***	(0.00)	-676.13*	(0.07)
Share of maize sold at harvest	1.35	(0.13)	-1.01	(0.58)	-869.23	(0.21)
Total Farm size (Ha)	-0.03	(0.30)	0.06	(0.51)	-2.41	(0.86)
Savings (x 1,000 F CFA)	-2E-04	(0.29)	-9E-04**	(0.05)	0.56	(0.17)
Age	0.22***	(0.01)	0.05	(0.73)	25.42	(0.68)
Age square	-0.002***	(0.01)	-7E-04	(0.63)	-0.24	(0.71)
=1 if Gender is male	1.10**	(0.03)	0.60	(0.60)	10.13	(0.98)
=1 if HH attended school	-0.30	(0.28)	-0.05	(0.91)	-166.45	(0.26)
Household size	-3E-03	(0.95)	-0.10	(0.25)	-43.01	(0.14)
Distance from market (Km)	-0.04	(0.28)	0.02	(0.71)	-42.74**	(0.04)
=1 if Input dealer in village	2.40**	(0.02)	1.57	(0.24)	656.87	(0.34)
=1 if extension agent in village	0.45	(0.21)	0.34	(0.52)	-15.75	(0.92)
Department dummies		YES		YES		YES
Time average		YES		YES		YES
Constant	-45.72***	(0.00)	-4.68	0.431	-2332.92	(0.39)

Observations	618	618	618
Pseudo R2	0.12		

*** p<0.01, ** p<0.05, * p<0.1