Gender bias in consumer perceptions: The case of agro-input dealers in Uganda

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June 22, 2022

Abstract

Faced with incomplete and imperfect information, economic actors rely predominantly on perceptions and often base decisions on heuristics prone to bias. Gender bias in perceptions favoring men has been found in a wide variety of settings and may be an important reason why some sectors remain dominated by men and gender gaps persist. Using ratings of agro-input dealers provided by smallholder farmers in their vicinity, we test if farmers perceive male-managed agro-input shops differently than agro-input shops managed by women. After controlling for observable characteristics at the input dealer level and including fixed effects to account for farmer-level heterogeneity, we find that farmers rate male-managed agro-input outlets higher on a range of attributes related to the dealership in general, as well as when farmers are asked to consider the quality of inputs sold by the dealer. Our results suggest that consumers' biased perceptions continue to be an important entry barrier for women in the subsector, and we conclude that policies and interventions designed to challenge gender norms and customs are needed to correct bias in perceptions.

1 Introduction

In the context of imperfect information, economic actors rely predominantly on perceptions and use mental shortcuts to make decisions using limited data (Kahneman, 2017). Reliance on instinct and emotions becomes dominant if it is difficult for economic actors to objectively assess the value of a commodity or service being bought and sold. However, perceptions and decision heuristics may suffer from a variety of cognitive biases such as stereotype thinking and availability bias, and may be influenced by social and cultural phenomena such as homophily effects and prevailing norms and customs.

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Agricultural inputs such as inorganic fertilizers or improved seed varieties lie somewhere on the continuum between experience goods and credence goods. When farmers inspect goods at the agro-input shop, the quality can only be assessed superficially from readily observable characteristics such as homogeneity of the seed or by checking if the fertilizer package is intact. Even after the commodity has been used and yields can be observed, it may still be difficult for the farmer to learn about the quality of the input, as many other factors in addition to the input affect yield. As such, when farmers decide to acquire agricultural inputs or not, perceptions and emotions often take the upper hand.

In addition to the the difficulty of judging quality of agricultural inputs, several studies note that there is considerable heterogeneity in the quality of inputs in the market. For instance, in Uganda, Bold et al. (2017) tested agricultural inputs purchased in local markets, and found that 30 percent of nutrient is missing in fertilizer, and hybrid maize seed is estimated to contain less than 50 percent authentic seeds. Also in Uganda, Ashour et al. (2019) tested herbicides and found that the average bottle in their sample was missing 15 percent of the active ingredient and 31 percent of samples contained less than 75 percent of the ingredient advertised. While it remains unclear if quality-related issues are due to deliberate adulteration or poor storage and handling, and at what point in the value chain quality starts to deteriorate, the resulting uncertainty makes reliance on perceptions and decision heuristics more likely (Barriga and Fiala, 2020).

In traditional societies with strong gender norms and customs, small businesses at different nodes along food supply chains are often one of the few options open to women to earn some money independently from their husband. While rapid urbanization has led to the emergence of fast-food restaurants, informal food vendors, who tend to be self-employed women, are still the main source of food for the majority of households (Giroux et al., 2021). And while supermarkets are emerging throughout the developing world, wet markets where mostly women sell produce continue to account for the majority of expenditure on fresh produce in many countries (Gorton, Sauer, and Supatpongkul, 2011). In Uganda, we find that a surprisingly large share of agro-input shops are operated and/or managed by women.

However, the same gender norms and customs may also mean that perceptions are stacked against women if they venture into certain areas such as agro-input provision. Farmers, both male and female, may be of the opinion that modern agricultural technologies are in the male domain. Furthermore, agro-input shops primarily deal in seed for semi-commercial crops such as maize or rice, as opposed to food security crops such as beans or cassava. Again, commercial crops are often considered to be the responsibility of the men, while women are assumed to take care of the household food supply (Orr et al., 2016; Dolan, 2001). As a result, we conjecture that female-managed agro-input shops may be disadvantaged when farmers form opinions about the quality of services rendered or goods sold.

In this paper, we test if farmers perceive agro-input shops managed by women less favorably than agro-input shops under male management using a unique dyadic dataset of farmer-dealer combinations. To operationalize perceptions, we asked farmer to rate agro-input dealers, on a scale of 1 to 5 on a range of characteristics. We then make between-dealer comparisons, accounting for observable differences in the quality of male- and female-managed shops. Furthermore, we use the fact that a farmer has generally rated more than one agro-input dealer. If the same farmer rates both male and female-managed agro-input shops, we can exploit this within-farmer variation and control for farmer specific observable and unobservable characteristics.

We find that farmers generally rate male-managed agro-input shops more favorably than agro-input shops managed by women. The difference in ratings is highest when farmers are asked to rate the agro-input dealership in terms of price competitiveness and in terms of reputation. We also find that seed from male-managed agro-input shops is rated higher than seed from shops managed by women. As the differences in ratings cannot immediately be explained by differences in the quality of the dealerships or the services and products they provide, we conclude that biased perceptions create an important disadvantage for female-managed agro-input shops.

In the remainder of this article, we first situate the research question in the wider literature. We then provide the context for the study and describe the main economic actors: agro-input dealers and smallholder maize farmers. We also describe how we measure perceptions, the key variable in this study. Next, we lay out the empirical strategy, followed by the results. A final section concludes and offers some policy guidance.

2 Research question and relation to the literature

We aim to test if gender equity bias—behavior that shows favoritism toward one gender over another—is present in the way smallholder maize farmers in southwestern Uganda perceive agro-input dealers in their neighborhood. Gender equity bias has been confirmed in a wide range of contexts, usually when people are asked to assess the performance of another person. Stereotyping and role congruence are often catalysts for distorted perceptions and false beliefs about the abilities of particular groups of people. We highlight some of the most important studies that search for systematic bias related to the gender of the person being assessed.

One area where gender equity bias has been studied extensively is in scientific publishing using peer review. For instance, Card et al. (2019) look at differences in rejection rates at four top economics journals. They compare male-authored papers to female-authored papers, using citations as a noisy measure of quality to account for potential sources of divergence between the two. They find that editors largely follow the referees, resulting in a 1.7 percentage point lower probability of a revise and re-submit verdict for papers with female authors relative to a citation-maximizing benchmark. However, evidence on gender biases in the evaluation of economic research remains mixed. For example, Chari and Goldsmith-Pinkham (2017) find no disparity in the acceptance rates of female- and male-authored papers for National Bureau of Economic Research (NBER) conferences; Hospido and Sanz (2021) do find a significant advantage for male authors being accepted at three different European conferences.

Gender equity bias has also been studied extensively in student evaluations of teaching. For instance, Mitchell and Martin (2018) find that the language students use in evaluations regarding male professors is significantly different than their language used in evaluating female professors. They also show that a male instructor administering an identical online course as a female instructor receives higher ordinal scores in teaching evaluations.

Gender equity bias is studied most in the context of peer review processes such as those mentioned above. However, the same perceptions surface when individuals decide on who to engage with, be it who to work with, who to elect as leaders, or who to consult. Labor markets and hiring decisions involve situations where managers decide based on limited information. Discrimination in labor markets, including discrimination related to gender, has been documented in several studies. Wu (2020) uses data from an online forum for economists called "Economic Job Market Rumors" to measure gender bias in discussions about women versus men. Gender equity bias is also often studied in the context of the wage gap, that is, when women appear to make substantially less money for the same work than their male counterparts. Often, this is also tied to gender equity bias in performance appraisals, where (often male) managers' beliefs creep into their evaluations of workers (Correll et al., 2020).

Gender equity bias is also pervasive in politics. Pair et al. (2021) use natural language processing (NLP) to search for gender bias in Kenya's leading newspaper and sentiment analysis to predict quantitative sentiment scores for sentences surrounding female leader names compared to male leader names. They find evidence of improvement in gender equality but also a backlash from increased female representation in high-level governmental leadership. Le Barbanchon and Sauvagnat (2021) find that female candidates obtain fewer votes in municipalities with higher gender earnings gaps. Klein, Shtudiner, and Zwilling (2021) find that a financial advisor's gender is one of the most important factors influencing a consumer's choice of investment advisor. Female advisors' gender was found to have a negative effect on the desire to invest, and this negative attitude was found to be significantly higher among male respondents.

Gender bias features so prominently in areas such as scholarly peer review, teaching assessments, or labour markets partly because perceptions are made explicit in the process, for instance through review reports, student feedback, or hiring committees. However, in economic transactions, gender biases remain hidden as perceptions are never measured. As a result, differences in outcomes are often attributed to various other causes, such as differences in education or ability between men and women.

3 Study Context

Our study area comprises 11 districts in southeastern Uganda, which roughly corresponds to the Busoga kingdom. In these districts, we carried out a census of all agro-input shops, which resulted in an effective sample size of about 350 dealers. Based on location, these agro-input shops were then grouped in catchment areas.[1] In some catchment

[1] A catchment area is defined as an area that is served by an agro-input dealer, that is, the area where the dealer's customers live. Agro-input shops are assigned to a catchment areas based on their geographic location, and thus the catchment areas of two or more

areas, there is a high density of agro-input dealers, while in others there are only one or two agro-input dealers. In each catchment area, we also sampled farmers in proportion to the number of agro-input dealers in the catchment area.

There is substantial heterogeneity among agro-input shops. Some are small informal shops located in rural areas, that sell other goods and only stock seed during the planting season. Others are located in towns or trading centers and specialize in farm inputs and tools. About 60 percent of the agro-input shop managers are male. The average shop has been in operation for about five years and serves about 40 customers a day, half of who come to buy maize seed. A shop stocks on average three maize seed varieties. Table 1 provides some descriptive statistics on the agro-input shops included in our study. More descriptive statistics describing seed handling and storage practices, efforts, and services of agro-input dealers, are presented in the appendix in Table 12.

The average farmer in our sample works on a small farm, with about 3.4 acres of land for crop production. Half of our sampled farmers indicate that they used improved maize seed on at least one plot in the season preceding the survey, and of the farmers that used improved seed, two-thirds obtained this seed from an agro-input shop. However, fertilizer use is very low. As a result, productivity is also low, with the average farmer harvesting only about 500 kg of maize per acre. Almost 70 percent of farmers are of the opinion that maize seed sold at the agro-input shop is counterfeit. Table 2 provides additional descriptive statistics of the farmers included in our study.

dealers overlap if these dealers operate in the same town, street, or right next to each other. Using the GPS coordinates of the dealers, we use the Haversine function to construct an adjacency matrix, and shops that are less than 5 km apart are grouped into a single catchment area. The 5 km threshold was selected based on visual inspection of the map, the size of an average village, and reported distances between farmers and dealers.

Table 1: Descriptive agro-input dealer statistics.

	mean	min	max	SD	nobs
Dealer's age in years	31.46	15	59	10.02	193
Dealer is male	0.591	0	1	0.493	193
Dealer finished secondary education	0.388	0	1	0.489	188
Dealer owns shop	0.565	0	1	0.497	193
Dealer received training on maize seed handling/storage	0.580	0	1	0.495	193
Shop's distance to nearest tarmac road in km	5.850	0	40	9.20	192
Distance between farmer and shop in km	49.109	3.87	124.435	25.10	193
Shop only sells farm inputs	0.751	0	1	0.433	193
Number of customers per day	44.55	2	300	48.34	192
Number of customers per day **buying maize seed**	23.01	0	250	28.25	192
Number of years since shop's establishment	5.430	0	33	6.106	193
Number of maize varieties in stock	3.057	0	10	1.948	193
Number of **hybrid** maize varieties in stock	1.803	0	8	1.476	193
Number of **OPV** maize varieties in stock	1.301	0	5	0.717	193
Sales price of maize seeds (per kilogram)	4353.674	2500	12000	1291.825	186
Cost of maize seed for dealer (UGX per kilogram)	3522.765	2000	8500	959.380	179
Amount of maize seed dealer bought (in kilograms)	969.978	0	52500	4683.849	184
Shop's cleanness/professionality rating by enumerator	3.503	1	5	1.142	193
Shop received seed-related complaint from customer	0.674	0	1	0.470	193
Shop's UNADA registration	0.489	0	1	0.501	182
Shop has trading license from local government	0.789	0	1	0.409	190

Table 2: Descriptive farmer statistics.

	mean	min	max	SD	nobs
Homestead's distance to nearest tarmac road in km	8.850	0	100	9.39	1844
Homestead's distance to village headquarters in km	0.744	0	12	0.899	1914
Homestead's distance to nearest agro-input shop in km	3.826	0	52	4.894	1858
Farmer's age in years	48.51	20	97	13.34	1923
Farmer is male	0.789	0	1	0.408	1931
Farmer is married	0.881	0	1	0.323	1931
Farmer finished primary education	0.525	0	1	0.500	1913
Number of people in household (incl. respondent)	8.651	1	25	4.029	1931
Years since farmer started growing maize	22.85	0	82	13.00	1931
Farmer is member of (maize) farmer group/association/cooperative	0.132	0	1	0.338	1927
Farmer's land for crop production in acres	3.350	0.25	80	3.980	1915
Land productivity in kg/acre (yield/area)	504.1	0	28000	842.5	1921
Farmer used improved maize seed (OPV/hybrid) for any field last season	0.499	0	1	0.500	1929
Farmer bought maize seed at agro-input shop (if he/she used improved seed)	0.671	0	1	0.470	932
Farmers thinks seed at agro-input shops is counterfeit/adulterated	0.684	0	1	0.465	1512
Farmer is satisfied with maize seed used on field	0.666	0	1	0.472	1931

4 Measuring perceptions

Quantifying perceptions of the quality of services provided by agro-input dealers and of the products they sell—improved maize seed varieties in particular—is central to our analysis. To do so, we asked farmers to rate agro-input dealers in their catchment area on a range of attributes. We broadly categorized the attributes into two families of indicators. A first set of indicators attempts to measure overall quality of agro-input dealers and the services they provide, while a second set of indicators has a much more narrow focus and asks about a particular product sold by the agro-input dealer (maize seed). Note that as agro-input dealers are often clustered in towns and trading centers, farmers often rate several agro-input dealers.

To measure the perceived quality of agro-input dealers, farmers were asked to rate these dealers on a scale of 1 to 5 on their general quality, location (convenience, accessibility, closeness to clients), price (competitive pricing, discounts), seed quality, stock (availability of seed, number of varieties in stock), and reputation (what do other farmers think about the dealer). We also compute an average of these six dealer level ratings. For these indicators, farmers were asked to rate the shop as a whole, which also includes the person who operates the shop.[2]

To measure the perceived quality of seed, farmers were asked to rate the improved maize varieties that dealers sell on a scale of 1 to 5 on their general quality, yield, drought tolerance, pest/disease tolerance, crop duration/maturation period, and germination reliability.[3] We also compute an average of these six seed-level ratings. For these variables, farmers were asked to rate seed, the product itself. Farmers were also allowed to indicate that they could not rate seed on a particular dimension (for instance because they never bought seed from the agro-input dealer).

We asked farmers to rate agro-input dealers twice, a first time in April 2021 and a second in January 2022. The average farmer in our dataset provided ratings for about two agro-input dealers, with some farmers rating up to 15 dealers. The average agro-input shop received ratings from almost 12 farmers, while one shop received ratings from almost 50 farmers. Table 3 provides descriptive statistics of the ratings used in our study.

[2] It may be that the shop is owned by a particular person, but the owner employs another person to manage the shop. This is especially the case for larger shops in towns. In villages and trading centers, the shop owner is generally also the manager.

[3] Some of these attributes are variety specific. For instance, some hybrid seeds may be particularly drought tolerant, while other seeds may be higher yielding. Therefore, we specifically asked farmers to rate varieties relative to what is advertised for these attributes.

Table 3: Descriptive agro-input dealer ratings.

	mean	min	max	SD	1st quartile	3rd quartile	nobs
Dealer's maize seed rating on general quality by farmers	3.799	1	5	0.873	3	4	992
Dealer's maize seed rating on yield by farmers	3.562	1	5	0.921	3	4	972
Dealer's maize seed rating on drought tolerance by farmers	3.018	1	5	0.882	2	4	937
Dealer's maize seed rating on pest/disease tolerance by farmers	2.464	1	5	0.945	2	3	949
Dealer's maize seed rating on speed of maturing by farmers	3.833	1	5	0.738	4	4	952
Dealer's maize seed rating rating on germination by farmers	3.676	1	5	0.898	3	4	967
Dealer's rating on general quality by farmers	3.734	1	5	1.006	3	4	1022
Dealer's rating on location by farmers	3.811	1	5	1.232	3	5	1022
Dealer's rating on price competitiveness by farmers	3.255	1	5	1.183	3	4	1022
Dealer's rating on seed quality by farmers	3.797	1	5	1.074	3	5	1022
Dealer's rating on maize seed stock by farmers	3.910	1	5	1.093	3	5	1022
Dealer's rating on reputation by farmers	4.162	1	5	0.937	4	5	1022

Note: The descriptives convey the dyadic nature of the dataset.

5 Empirical Strategy

Our empirical strategy exploits the particular nature of the data, that is, that each farmer in our dataset rates several agro-input dealers (and each dealer is rated by several farmers). A useful starting point is the following specification[4]:

$$y_{f,d} = \alpha + \beta g_d + \varepsilon_{f,d} \tag{1}$$

Here, $y_{f,d}$ represents the rating, on a scale of 1 (poor) to 5 (excellent), given by farmer f to agro-input dealer d. g_d is the main variable of interest—the gender of dealer d. α and β are parameters to be estimated, and $\varepsilon_{f,d}$ is a residual.

Because the same farmer may rate several agro-input dealers, we cannot assume that the ratings $y_{f,d}$ in equation 1 are independent. For example, the ratings that a farmer provides may be affected by a (potentially unobservable) characteristic of the farmer (e.g., a poor experience with an agro-input dealer in a previous year), which may affect the ratings received by all agro-input dealer rated by this particular farmer. Furthermore, the same agro-input dealer may be rated by several farmers, leading to interdependence in the other dimension. For example, the ratings that an agro-input dealer receives may be affected by a (potentially unobservable) characteristic of the dealer (e.g., dealer friendliness), which may affect the ratings given by all farmers that rated this particular dealer. To account for this two-way interdependence in equation 1, we define a composite error term, ($\varepsilon_{f,d}$) that can be decomposed into a farmer specific component (ν_f), an agro-input dealer specific component (ω_d), and a residual ($\epsilon_{f,d}$) that varies at the level of the farmer-dealer interaction.

$$\varepsilon_{f,d} = \nu_f + \omega_d + \epsilon_{f,d} \tag{2}$$

Equation 2 shows that the dyadic nature of our data leads to two-way clustering in the error term. As long as the error term is uncorrelated with the explanatory variable(s) included in equation 1, Ordinary Least Squares (OLS) remains consistent. However, not taking into account within-cluster error correlation generally leads to standard errors that are biased downward, leading to under-rejection of the null hypothesis that gender does not affect ratings. In our case, it should be noted that clustering is non-nested. As traditional cluster-robust inference can only deal with clustering in one of the dimensions, our strategy will consist of including sufficient regressors to minimize concerns about error correlation at the agro-input dealer level, and then cluster standard errors at farmer level (Cameron and Miller, 2015).

To test for an agro-input dealer gender effect, we can simply compare average ratings received by male-managed

[4] To keep notation simple, we omit the time subscript, even though as mentioned in Section 4 , farmers were asked to rate agro-input dealers twice.

agro-input shops to average ratings received by female-managed agro-input shops. Equation 3 shows how this can be done using a simple OLS regression on dealer-level averages.

$$\frac{1}{F}\sum_{f} y_{f,d} = \alpha + \beta\frac{1}{F}\sum_{f} g_d + \frac{1}{F}\sum_{f}\nu_f + \frac{1}{F}\sum_{f}\omega_d + \frac{1}{F}\sum_{f}\epsilon_{f,d} \tag{3}$$

$$\overline{y}_d = \mu + \gamma g_d + \overline{\varepsilon}_d \tag{4}$$

In equation 3, identification of the gender equity effect (β) relies on differences between agro-input dealers. As dealer gender is constant for all farmers that rate a particular dealer, the average g_d is also a binary indicator of the gender of that particular dealer d. The farmer-specific component ν_f is absorbed in the intercept term μ, while the dealer specific-component ω_d is now included in the error term $\overline{\varepsilon}$.

It is important to note that in equation 4, the error component $\frac{1}{F}\sum_{f}\omega_d$ in the error term $\overline{\varepsilon}_d$ may be correlated with the independent variable g_d. This would be the case if, for example, female agro-input shop managers are on average less educated than male agro-input shop managers, and less educated agro-input dealers are rated lower by farmers. In this case, differential ratings are not caused by gender in itself, but rather driven by differences in education. We will control for a range of agro-input dealer-level potential confounders by including them as additional regressors (x_d) in equation 4:

$$\overline{y}_d = \mu + \gamma g_d + \varphi x_d + \overline{\varepsilon}_d \tag{5}$$

As we are interested in explaining gender equity bias in perceptions in different dimensions, the set of control variables used will also differ. For example, when farmers are asked to rate agro-input dealers in terms of price competitiveness, it seems reasonable to include prices charged by dealers as controls. Similarly, for perceptions related to the quality of seed sold, we are particularly interested in testing if the coefficient on the gender of the agro-input dealer changes after adjusting for various observable dealer characteristics that are directly related to quality, such as storage technology, infrastructure such as leak-proof roof or insulation, etc. In this way, we attempt to differentiate between situations where farmers perceive female-managed agro-input shops less favorably and situations where differences in ratings reflect real differences between male- and female-managed shops.

Farmer-level characteristics could also confound the relationship between an agro-input dealer's gender and the rating that the farmer provides. For example, it may be that farmers who are better educated generally provide higher ratings. At the same time, it may be that better-educated farmers are more inclined to shop at male-managed agro-input dealerships. This makes it difficult to differentiate a gender equity effect from an effect arising from differences in education of the farmer. Fortunately, we often have instances where the same farmer rates both male- and female-managed agro-input shops. This allows us to exploit within-farmer variation for identification. While we would be able to control for a farmer's education level by simply including it in an OLS regression, a within-farmer transformation also controls for characteristics that would be difficult or impossible to measure and to control for, like motivation, kindness, locus of control, norms and values, etc. In other words, the within-farmer (fixed effects) estimator removes all farmer-level heterogeneity.

$$y_{f,d} - \frac{1}{D}\sum_{d} y_{f,d} = \beta \left(g_{f,d} - \frac{1}{D}\sum_{d} g_{fd} \right) + \left(\varepsilon_{f,d} - \frac{1}{D}\sum_{d} \varepsilon_{f,d} \right) \tag{6}$$

$$y_{f,d} - \overline{y}_f = \gamma \left(g_{f,d} - \overline{g}_f \right) + \varepsilon_{f,d} \tag{7}$$

Finally, we will also run a fixed effects model that, in addition to controlling for farmer heterogeneity through fixed effects, also controls for dealer-level observable characteristics. We will again do this by including additional regressors (x_d) in equation 7, which leads to:

$$y_{f,d} - \overline{y}_f = \gamma \left(g_{f,d} - \overline{g}_f \right) + \varphi \left(x_{f,d} - \overline{x}_f \right) + \varepsilon_{f,d} \tag{8}$$

6 Results

Table 4 reports differences in perceived agro-input dealer quality between male- and female-managed agro-input outlets using an OLS regression based on equation 4. We find that on all but one dimension, male-managed agro-input shops are rated higher than female-managed shops, and the difference in rating is significant for five out of the seven comparisons (at a 10 percent significance level). The largest difference is found when farmers are asked to rate price competitiveness. Here, female-managed agro-input shops are scored only 3.237 out of 5, while male-managed agro-input shops receive a score of 3.437 out of 5. Equally large differences exist when farmers are asked to rate an agro-input dealer in terms of product availability. Here, male-managed agro-input shops receive an average score of almost 4 out of 5, while female dealers get 3.792. Interestingly, female-managed agro-input shops are not rated significantly worse with regards to the quality of seed sold. They also appear to be equally rated with respect to location.

Table 5 repeats the between-dealers analysis, but compares ratings for quality attributes of seed sold by the dealers. While we still find that on most characteristics, male-managed agro-input shops get a higher rating than female-managed agro-input shops, the differences are never significant. Note that these results are consistent with what was found in Table 4, where we also failed to find a significant difference when asking about seed quality. This suggests that when farmers are asked to think about a particular product, they make abstraction of the person selling it, and the gender effect becomes less important.

Table 4: Between-dealers model focusing on dealer ratings (control variables not included).

	Dependent variable: Average rating received by dealer						
	Average dealer rating	Dealer's general quality	Dealer's location	Dealer's price	Dealer's seed quality	Dealer's stock	Dealer's reputation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	3.764	3.738	3.89	3.237	3.878	3.792	4.051
	(0.05)	(0.06)	(0.086)	(0.071)	(0.064)	(0.077)	(0.064)
Dealer is male	0.109^{*}	0.129^{*}	-0.085	0.2^{**}	0.052	0.199^{**}	0.161^{**}
	(0.063)	(0.075)	(0.109)	(0.089)	(0.081)	(0.097)	(0.081)
Number of obs.	152	152	152	152	152	152	152

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Note: Here, the gender of the dealer is a dummy variable where 1 is male and 0 is female. The ratings received by the dealers are averaged at the dealer level. Standard errors are presented in ().

Table 5: Between-dealers model focusing on seed ratings (control variables not included).

	Dependent variable: Average rating received by dealer						
	Average seed rating	Seed's general quality	Seed's yield	Seed's drought tolerance	Seed's pest/disease tolerance	Seed's speed of maturing	Seed's germination
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	3.417	3.87	3.592	3.005	2.683	3.716	3.651
	(0.044)	(0.051)	(0.059)	(0.061)	(0.062)	(0.055)	(0.066)
Dealer is male	0.053	0.058	0.066	−0.03	0.011	0.081	0.104
	(0.056)	(0.064)	(0.075)	(0.077)	(0.078)	(0.068)	(0.083)
Number of obs.	152	152	152	150	152	151	152

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Note: Here, the gender of the dealer is a dummy variable where 1 is male and 0 is female. The ratings received by the dealers are averaged at the dealer level. Standard errors are presented in ().

Results of between-dealer regressions with added control variables (see equation 5) are presented in Table 6 for the more general ratings of dealer characteristics and in Table 7 for ratings directly related to seed quality. In all regressions, we add dealer age and dealer education level as general control variables, and additional controls depending on the attribute being rated.

In the first column of Table 6, we again explain the overall dealer rating. As this is an average of all the other attributes, we also include most controls in this regression, nine in addition to dealer age and education. The rationale for including each control is provided below in the discussion of the regressions for each rating attribute. We find that, even after controlling for a range of observable indicators for overall quality differences between male- and female-managed agro-input shops, male-managed shops are rated significantly higher by consumers.

The second column of Table 6 corresponds to the second column of Table 4, which compares average general quality ratings given to male- versus female-managed agro-input shops. We have three relatively objective observable proxies for general dealership quality. First, we asked enumerators to provide an overall cleanness and professionality rating for the agro-input shop for which they collected data. Second, we construct an index that measures dealer effort and a range of services that dealers offer to clients.[5] In particular, this index accounts for whether an agro-input dealer 1) always explains how seed should be used (seed spacing, seed rate, complementary inputs); 2) always recommends complementary inputs such as fertilizers and chemicals; 3) provides extension/training to clients on how to use improved seed varieties; 4) provides discounts to clients who buy large quantities of seed; 5) sells small quantities; 6) provides seed on credit; 7) has received a seed-related complaint from a customer; and 8) accepts mobile money as a payment modality. Descriptive statistics for the variables which constitute this effort and service index are shown in the appendix in Table 12. Third, we asked enumerators to carefully observe and note down a range of capital-intensive seed handling and storage practices, which were also summarized in an index. In this index, we account for whether 1) the roof is leak-proof; 2) the roof is insulated to keep the heat out; 3) the walls are insulated to keep the heat out; 4) the area where seed is stored is properly ventilated; 5) any official certificates are on display in the shop (e.g., inspection certificates, training certificates, registration with association, etc). Also for these variables which constitute the capital-intensive practices index, descriptive statistics are shown in the appendix in Table 12. We see that after controlling for these three groups of variables, the male premium on general quality ratings increases from 0.13 to 0.16. Note that the index of capital-intensive seed handling and storage practices observed by the enumerator is significant and has the expected sign, as input dealers who score better on this index also receive higher scores on general dealership quality.[6]

When farmers were asked to assess agro-input dealers in terms of their location, the average distance between

[5] Indices were created by weighing each component by the inverse covariance matrix, constructed following Anderson (2008).

[6] However, caution should be taken when interpreting control variables, as control variables do not necessarily have a structural interpretation. For instance, it may be that the relationship between the control variable and the outcome variable is confounded by a third (potentially unobservable) variable (Hünermund and Louw, 2020).

dealers and their customers,[7] capturing some indication of centrality of the dealer, provides an obvious candidate as a control variable (third column in Table 6). We do not find a gender equity effect on ratings concerning location in Table 4, nor do we find a difference after controlling for centrality. It should also be noted here that the control variable is significant in the expected direction, as dealers for whom the average distance between dealer and customer is higher (or centrality is lower) also are scored lower in terms of location.

In the fourth column of Table 6, we look at price competitiveness again. To account for the possibility that the difference in price ratings between male- and female-managed agro-input shops is driven by actual price differences between these shops, we control for the average price charged by the dealer, as well as for the cost at which the dealer obtains seed (which is an important determinant of the price). The analysis confirms that there is a difference in perception of male and female dealers, and that this difference is not due to actual price differences. The gender equity effect is similar in size to the one found without controlling for actual price differences in Table 4. Note again that one of the control variables is significant and suggests that dealers who charge higher prices also receive significantly lower price competitiveness ratings.

In the fifth column of Table 6, we control for another index, one that reflects all seed handling and storage practices observed by the enumerator. This index includes the five capital-intensive practices mentioned above, but also accounts for whether the agro-input dealer 1) destroys seed that has exceeded shelf-life; 2) stores seed in a dedicated area, away from other merchandise; 3) has no problem with rats, insects, or other infestations; 4) stores seed in ambient light conditions as recommended; 5) stores seed on pallets or shelves; and 6) does not store seed in open bags or open containers. This index also includes the shop's overall cleanness and professionality rating provided by the enumerator. Again, descriptive statistics for the variables which constitute this all (i.e. capital- and labor intensive) practices index can be found in the appendix in Table 12. As in column 5 of Table 4, we do not find a gender equity effect regarding the seed quality rating after controlling for observable quality indicators.

In the sixth column, we repeat the analysis for perceptions related to a dealers' stock, now controlling for the number of hybrid maize varieties that this dealer has in stock and the quantity bought by the dealer from seed producers or wholesalers, the former being significant and having the expected sign. The male premium on the rating persists, although the effect becomes slightly weaker as compared to a regression without controls (column 6 in Table 4).

The analysis regarding reputation is repeated in column 7, now controlling for the number of years the shop has been in business, and whether the shop is registered with the Uganda National Agro-input Dealer Association (UNADA), as we expect both to have an impact on a dealer's reputation. Here we also see that male dealers receive

[7] The Haversine formula calculating the arc distance between two points on Earth is used. The latitudes and longitudes are extracted from the GPS coordinates for both farmers and agro-input shops and inserted as paired values in the Haversine formula. This formula then calculates the distances between these paired latitudes and longitudes in meters, following which we obtain the distances in kilometers and standardize the variable.

higher scores even after controlling for experience and UNADA registration, with the effect becoming slightly weaker (as compared to column 7 in Table 4).

Table 7 repeats the between dealer analysis for quality attributes of maize seed sold by the agro-input shops reported in Table 5, but controls for practices that are expected to improve seed quality. As all ratings in Table 5 concern quality, we include the same control in all regressions. We use the most elaborate index of all seed handling and storage practices as observed by the enumerator that was also used in model (5) of Table 6. Recall from Table 5 that we did not find a gender equity effect for any seed-quality-related dimensions, and adding the index to control for quality does not change this. Note that the index is generally positively correlated with the rating, but only significantly so when farmers are asked to assess the seed's yield.

Overall, comparing Table 6 to Table 4 and Table 7 to Table 5, we notice that results, both in terms of parameter estimates for β and their significance, are very similar. This suggests that differences between male- and female-managed agro-input shops reflect structural differences in perception of the two genders, rather than actual differences in the dimension being rated (quality, price competitiveness, stock, and reputation).

Tables 8 and 9 show parameter estimates for an indicator variable that takes the value of one if the agro-input dealer is male, estimated using a model that includes farmer fixed effects (using the within transformation of equation 6).[8] In Table 8, we use the general agro-input dealer ratings as outcome variables, similar to Table 4. Table 9 estimates the same model, but now for the more specific seed-quality-related ratings, similar to Table 5.

[8]As errors are also correlated within agro-input dealers, we report standard errors that are robust to clustering in this dimension.

Table 6: Between-dealers model focusing on dealer ratings (control variables included).

	Dependent variable: Average rating received by dealer						
	Average dealer rating	Dealer's general quality	Dealer's location	Dealer's price	Dealer's seed quality	Dealer's stock	Dealer's reputation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	3.797	3.77	3.829	3.326	3.822	3.647	3.921
	(0.135)	(0.227)	(0.196)	(0.169)	(0.15)	(0.204)	(0.156)
Dealer is male	0.155**	0.161**	−0.068	0.219**	0.057	0.183*	0.158*
	(0.063)	(0.071)	(0.106)	(0.091)	(0.081)	(0.097)	(0.082)
Dealer's age in years	−0.002	−0.003	0.003	−0.003	−0.001	−0.001	0
	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
Dealer finished secondary education	0.119	0.144	−0.056	−0.01	0.198**	0.092	0.15
	(0.079)	(0.088)	(0.129)	(0.108)	(0.098)	(0.122)	(0.1)
Shop's cleanness/professionality rating by enumerator		−0.005					
		(0.047)					
Index of dealer's efforts and services	0.172*	0.152					
	(0.101)	(0.11)					
Index of capital-intensive seed handling/storage practices observed by enumerator		0.29***					
		(0.079)					
Standardized distance between farmer and shop	−0.072*		−0.242***				
	(0.041)		(0.064)				
Standardized sales price of maize seed	−0.101*			−0.176**			
	(0.052)			(0.074)			
Standardized cost of maize seed for dealer	0.072			0.085			
	(0.052)			(0.072)			
Index of all seed handling/storage practices observed by enumerator	0.082				0.184		
	(0.103)				(0.118)		
Number of hybrid maize varieties in stock	−0.033					0.07*	
	(0.029)					(0.038)	
Standardized amount of maize seed dealer bought	−0.016					0.062	
	(0.028)					(0.041)	
Number of years since shop's establishment	−0.001						0.002
	(0.006)						(0.007)
Shop's UNADA registration	0.12						0.113
	(0.096)						(0.103)
Number of obs.	149	151	152	151	151	152	152

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Note: Here, the gender of the dealer is a dummy variable where 1 is male and 0 is female. The ratings received by the dealers are averaged at the dealer level. Standard errors are presented in ().

Table 7: Between-dealers model focusing on seed ratings (control variables included).

	Dependent variable: Average rating received by dealer						
	Average seed rating	Seed's general quality	Seed's yield	Seed's drought tolerance	Seed's pest/disease tolerance	Seed's speed of maturing	Seed's germination
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	3.416	3.768	3.584	3.128	2.779	3.644	3.612
	(0.105)	(0.12)	(0.139)	(0.147)	(0.147)	(0.131)	(0.157)
Dealer is male	0.053	0.047	0.066	−0.019	0.023	0.075	0.104
	(0.057)	(0.065)	(0.075)	(0.079)	(0.079)	(0.07)	(0.085)
Dealer's age in years	−0.002	0.002	−0.001	−0.005	−0.005	0.002	−0.001
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Dealer finished secondary education	0.125^{*}	0.122	0.118	0.058	0.188^{*}	0.052	0.175^{*}
	(0.069)	(0.079)	(0.091)	(0.096)	(0.096)	(0.085)	(0.103)
Index of all seed handling/storage practices observed by enumerator	0.061	0.139	0.194^{*}	0.064	−0.089	0.083	−0.016
	(0.083)	(0.095)	(0.11)	(0.115)	(0.115)	(0.102)	(0.124)
Number of obs.	151	151	151	149	151	150	151

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Note: Here, the gender of the dealer is a dummy variable where 1 is male and 0 is female. The ratings received by the dealers are averaged at the dealer level. Standard errors are presented in ().

Table 8: Farmer fixed-effects model focusing on dealer ratings (control variables not included)

	Dependent variable: Rating of a particular farmer given to a particular dealer						
	Average dealer rating	Dealer's general quality	Dealer's location	Dealer's price	Dealer's seed quality	Dealer's stock	Dealer's reputation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dealer is male	0.116^{***}	0.176^{***}	0.023	0.188^{***}	0.049	0.082^{*}	0.18^{***}
	(0.029)	(0.05)	(0.048)	(0.047)	(0.043)	(0.05)	(0.048)
Number of obs.	3562	3562	3562	3562	3562	3562	3562

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Note: Here, the gender of the input dealer is a dummy variable carrying the value of either 0 or 1. Fixed effects or within estimation has been used at the farmer level. Cluster-robust SE are obtained by clustering at the dealer level (presented in ()).

Table 8 shows that male-managed agro-input outlets receive significantly higher ratings in the areas of quality in general, price competitiveness, stock, and reputation. The average rating also shows a significant difference between male and female dealers. Comparing Table 8 to Table 4, the largest difference can still be found for price competitiveness, even though the magnitude of the effect decreased somewhat. The effect of gender on ratings related to stocks reduced sharply after controlling for farmer-level heterogeneity.

For seed-quality-specific ratings, comparing Table 9 to Table 5, we see that, after controlling for farmer-level heterogeneity, some of the differences between male and female dealers turn significant. For perceptions related to seed germination, male-managed agro-input shops receive a score that is on average 0.11 higher than the germination rating female-managed shops receive. We further find signs of gender effects when farmers are asked to rate seed quality in general and whether seed maturity is as advertised. The gender equity bias in these dimensions is also reflected in a significant difference in the average seed rating between male- and female-managed agro-input shops (column 1).

The fact that we do find gender equity bias when farmers are asked to assess seed quality if we control for farmer fixed effects suggests that, in the between-dealer regressions of Tables 5 and 7, gender equity bias is obscured by farmer-level confounders. For instance, it could be that farmers that are better educated also provide higher ratings and that these better educated farmers are also more likely to shop at female managed dealerships. Not controlling for differences in education levels of farmers may then lead to an underestimation of discrimination against female-managed agro-input shops.

Finally, we run a fixed effects model that, in addition to controlling for farmer heterogeneity, also controls for dealer-level observable characteristics (see equation 8), similar to Tables 6 and 7. Table 10 presents the more general dealer ratings, and Table 11 presets the seed quality ratings.

We find that controlling for observable characteristics at the dealer level does not change findings for the first set of ratings, which evaluate the agro-input dealer. The largest gender equity effects are found when farmers are asked to rate agro-input dealer reputation (column 7) and price competitiveness (column 4). In both cases male-managed agro-input shops are rated about .2 points higher. The difference in ratings between male- and female-managed agro-input shops for the stock attribute has become indistinguishable from zero.

Comparing Tables 9 and 11, the significant differences between male- and female-managed agro-input shops with respect to the seed maturity rating (column 6), germination rating (column 7), and general seed quality ratings (column 2) found in Table 9 persist after controlling for observable dealer-level differences in seed quality.

Table 9: Farmer fixed-effects model focusing on seed ratings (control variables not included)

	Dependent variable: Rating of a particular farmer given to a particular dealer						
	Average seed rating	Seed's general quality	Seed's yield	Seed's drought tolerance	Seed's pest/disease tolerance	Seed's speed of maturing	Seed's germination
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dealer is male	0.073^{***}	0.075^{*}	0.047	0.053	0.041	0.079^{*}	0.11^{***}
	(0.027)	(0.038)	(0.043)	(0.042)	(0.044)	(0.039)	(0.04)
Number of obs.	3520	3496	3442	3356	3384	3398	3428

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Note: Here, the gender of the input dealer is a dummy variable carrying the value of either 0 or 1. Fixed effects or within estimation has been used at the farmer level. Cluster-robust SE are obtained by clustering at the dealer level (presented in ()).

Table 10: Farmer fixed-effects model focusing on dealer ratings (control variables included)

	Dependent variable: Rating of a particular farmer given to a particular dealer						
	Average dealer rating	Dealer's general quality	Dealer's location	Dealer's price	Dealer's seed quality	Dealer's stock	Dealer's reputation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dealer is male	0.118***	0.149**	0.026	0.2***	0.03	0.082	0.201***
	(0.034)	(0.058)	(0.049)	(0.05)	(0.047)	(0.051)	(0.048)
Dealer's age in years	0.003**	0.001	0	0.003**	0.004***	0.004***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dealer finished secondary	0.012	0.043	0.029	−0.034	0.037	−0.007	−0.003
education	(0.025)	(0.036)	(0.035)	(0.036)	(0.037)	(0.036)	(0.032)
Shop's cleanness/professionality		0.021					
rating by enumerator		(0.015)					
Index of dealer's efforts	0.009	−0.004					
and services	(0.029)	(0.043)					
Index of capital-intensive seed handling/storage		0.057*					
practices observed by enumerator		(0.031)					
Standardized distance between	0.004		0.004				
farmer and shop	(0.01)		(0.014)				
Standardized sales price	−0.023*			0.009			
of maize seed	(0.013)			(0.02)			
Standardized cost of maize	0.02			−0.009			
seed for dealer	(0.014)			(0.02)			
Index of all seed handling/storage	−0.008				0.072*		
practices observed by enumerator	(0.024)				(0.04)		
Number of hybrid maize	−0.008					0.001	
varieties in stock	(0.008)					(0.011)	
Standardized amount of maize	−0.002					0.013	
seed dealer bought	(0.008)					(0.013)	
Number of years since	0.006**						0.015***
shop's establishment	(0.002)						(0.003)
Shop's UNADA	−0.031						0.002
registration	(0.026)						(0.031)
Number of obs.	2779	3014	3433	3302	3149	3356	3433

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Note: Here, the gender of the input dealer is a dummy variable carrying the value of either 0 or 1. Fixed effects or within estimation has been used at the farmer level. Cluster-robust SE are obtained by clustering at the dealer level (presented in ()).

Table 11: Farmer fixed-effects model focusing on seed ratings (control variables included)

	Dependent variable: Rating of a particular farmer given to a particular dealer						
	Average seed rating	Seed's general quality	Seed's yield	Seed's drought tolerance	Seed's pest/disease tolerance	Seed's speed of maturing	Seed's germination
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dealer is male	0.073^{**}	0.073^{*}	0.07	0.032	0.044	0.087^{*}	0.084^{*}
	(0.029)	(0.041)	(0.046)	(0.044)	(0.049)	(0.042)	(0.043)
Dealer's age in years	0.001	0.003^{**}	0.004^{***}	−0.001	−0.001	0	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Dealer finished secondary education	−0.022	−0.023	−0.029	0.009	0.011	-0.084^{***}	0.011
	(0.02)	(0.029)	(0.032)	(0.031)	(0.033)	(0.028)	(0.032)
Index of all seed handling/storage practices observed by enumerator	0.023	0.051	0.062^{*}	−0.009	−0.029	0.035	0.033
	(0.022)	(0.033)	(0.035)	(0.033)	(0.035)	(0.03)	(0.033)
Number of obs.	3109	3088	3038	2965	2988	3000	3026

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Note: Here, the gender of the input dealer is a dummy variable carrying the value of either 0 or 1. Fixed effects or within estimation has been used at the farmer level. Cluster-robust SE are obtained by clustering at the dealer level (presented in ()).

7 Conclusion and policy implications

Using survey data from smallholder farmers and agro-input dealers in southeastern Uganda, we tested if farmers perceive female-managed agro-input shops differently than male-managed agro-input shops. To do so, we asked a random sample of farmers to rate agro-input dealers in their immediate neighborhood on a scale ranging from 1 (poor) to 5 (excellent). In addition to asking farmers to rate agro-input dealers on a set of general characteristics such as accessibility and price competitiveness, we also asked them to focus on a particular product that these agro-input dealers sell (maize seed), and to rate this product on various dimensions like germination, yield, etc.

Using simple comparisons of average ratings given to male- and female-managed agro-input shops, we found that female-managed shops are generally rated lower than their male-managed counterparts. However, when farmers were asked to focus on a specific product, the difference became insignificant. When adding controls for agro-input dealer-level observable characteristics, parameter estimates and significance remained similar, suggesting that differences in ratings between male- and female-managed agro-input shops reflect structural differences in perceptions rather than actual differences.

However, ratings of agro-input dealers provided by farmers may also be influenced by farmer characteristics. To control for farmer heterogeneity, we exploited the fact that farmers often rated several agro-input dealers of different genders, and ran farmer fixed effects models. In doing so, we confirmed the existence of gender equity bias when farmers were asked to rate general characteristics of agro-input dealers, but also found differences in ratings of different dimensions of seed quality sold by dealers of different genders.

Looking into the individual dimensions that were rated, we find particularly strong gender equity bias when farmers were asked to rate agro-input dealers in terms of price competitiveness. Furthermore, and especially after controlling for farmer-level heterogeneity, we find male-managed agro-input shops to have significantly better reputation than female shops. This difference in reputation is also reflected in a significant difference between male and female dealers in the general quality rating. On the other hand, we do not find that male- and female-managed agro-input shops were rated differently when farmers were asked to consider location. This may be because location is easier to assess objectively. For attributes related to the quality of seed sold by agro-input dealers, gender equity bias was largest when farmers were asked to assess seed germination rates and whether the seed being rated had the advertised maturing period.

The prevalence of gender equity bias in the context of agro-input dealers again underscores the importance of customs and norms in rural societies. Interventions and initiatives that focus solely on increasing women's empowerment are unlikely to be sufficient, and may in some cases even backfire (Pair et al., 2021). It will be important to challenge gender stereotypes and role congruence and such interventions should not focus on only one gender.

Gender norms and customs prevent women from aspiring and developing an internal locus of control. To overcome this, role models have been found particularly effective in raising aspirations. For example, Porter and Serra (2020) find that successful and charismatic women who majored in economics at the same university led to an increase in girls choosing economics as a major. Role model effects may also emanate from fictional characters. For example, Riley (2022) shows how the female protagonist in a feel-good Disney movie impacts secondary school students' exam performance in Uganda. This opens the prospect of using mass media to influence gender roles and customs (La Ferrara, Chong, and Duryea, 2012).

Gender roles and customs also indirectly prevent women from realizing their full potential, as men may not support (or may even prevent) participating of women and girls in male-dominated sectors. However, social norms are also perceived by individuals. Sometimes, men prevent their wives from participating in the economy because they think it will be frowned upon by their peers. In cases where perception is inaccurate, simply correcting this perception may be effective. For example, Bursztyn, González, and Yanagizawa-Drott (2020) find that in Saudi Arabia, a country with strict norms and traditions on women's mobility, many men overestimate the severity of peer judgment if their wives work outside of the house. Correcting this false perception led to a significant increase in women's employment. Role models can also be important to challenge beliefs and stereotypes about lesser abilities of one group held by another group: Beaman et al. (2009) show that the appointment of women leaders to Indian village councils improved men's perceptions of women's leadership abilities.

In addition to underscoring the importance of gender norms and customs in shaping perceptions, our study serves to draw specific lessons for policy. We restrict ourselves to three areas where our findings can be operationalized.

First, even though we find no evidence of actual differences in quality between male- and female-managed agro-input shops, existing training and advisory services for agro-input dealers are likely to be biased toward men. Ensuring that women entrepreneurs have access to, and benefit from, training should be an important policy priority. The effectiveness and inclusiveness of training programs depend on many attributes of the program. This includes more obvious aspects such as the content of what is taught in the training and who is targeted, but also less obvious attributes such as the gender of who provides the training, timings of training, etc. However, it is also important to change the perception that female-managed agro-input shops are likely to receive less training. This could be achieved by making training attendance publicly visible, perhaps through a register of trained agro-input dealers, through certificates that are posted in the shops, etc. such that equal capactity between male- and female-managed agro-input shops becomes more apparent to clients.

Second, the share of women among opinion leaders and experts in the sector needs to increase. In light of the emerging evidence of the importance of role models, the presence of women among agro-input dealers, inspectors, and leadership of professional associations such as UNADA needs to increase. For public sector positions, quota's may be considered.

Finally, we find that biased perceptions exist especially with respect to prices charged by agro-input dealers. Simply advertising prices may be sufficient to make prices objectively verifiable, and customers will need to depend less on perceptions and the use of mental shortcuts that are prone to gender equity bias.

Acknowledgments

This research was partly funded by the CGIAR Research Program on Policies, Institutions, and Markets (PIM), led by the International Food Policy Research Institute (IFPRI) and carried out with support from the CGIAR Fund contributors (https://www.cgiar.org/funders/). The authors also acknowledge financial support from The Netherlands – CGIAR research programme on Seed Systems Development, grant number W08.240.105, funded by the Netherlands Organisation for Scientific Research (NWO-WOTRO). We thank Richard Ariong, Leocardia Nabwire, Wilberforce Walukano and Marc Charles Wanume for excellent field support. The analysis is the sole responsibility of the authors, and does not reflect the views of any funding agency or organization mentioned here.

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Appendix

Table 12: Descriptive agro-input dealer statistics: Variables in indices

	mean	min	max	SD	nobs
Capital-intensive seed handling/storage practices observed by enumerator					
Shop has leak-proof roof	0.539	0	1	0.500	193
Shop has insulated roof	0.617	0	1	0.487	193
Shop has insulated walls	0.813	0	1	0.391	193
Shop is ventilated	0.834	0	1	0.373	193
Shop displays official certificate	0.503	0	1	0.501	193
Shop always handles expired seed correctly	0.941	0	1	0.237	185
Labor-intensive seed handling/storage practices observed by enumerator					
Shop stores seed away from other products	0.404	0	1	0.492	193
Shop has problem with pests	0.637	0	1	0.482	193
Shop's light is ambient (not direct sunlight/dark)	0.819	0	1	0.386	193
Shop stores seed on pallets/shelves (not directly on wood/floor/cardboard)	0.697	0	1	0.461	185
Shop stores maize seed in open containers	0.192	0	1	0.395	193
Shop's cleanness/professionality rating by enumerator	3.503	1	5	1.142	193
Dealer's efforts and services					
Shop always explains to customers how seed should be used	0.472	0	1	0.500	193
Shop always recommends complementary inputs to customers	0.549	0	1	0.499	193
Shop offers extension/training	0.523	0	1	0.501	193
Shop offers discounts for large quantities	0.772	0	1	0.421	193
Shop's smallest seed bag is 1 kg (not larger)	0.728	0	1	0.446	184
Shop provides seed on credit	0.648	0	1	0.479	193
Shop received seed related complaint from customer	0.674	0	1	0.470	193
Shop accepts mobile money as payment	0.399	0	1	0.491	193