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

Anusha De*, Caroline Miehe *, and Bjorn Van Campenhout†*

June 6, 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 are dominated by men and gender gaps persist. Using ratings provided by smallholder farmers of agro-input dealers in their vicinity, we test if farmers perceive male managed agro-input shops differently than agro-input shops managed by a woman. After controlling for input dealer level observable characteristics 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 biased perceptions by consumers continue to be an important entry barrier for women in the sub-sector, and we conclude that policies and interventions designed to challenge gender norms and customs are needed to correct bias in perceptions.

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 the commodity or service being transacted. However, perceptions and decision heuristics may suffer from a variety of cognitive biases such as stereotype thinking, and may be influenced by social and cultural phenomena such as homophily effects and prevailing norms and customs.

Agricultural inputs such as inorganic fertilizer or improved seed varieties lie somewhere on the continuum between experience goods and credence goods.

*LICOS Center for Institutions and Economic Performance, KULeuven, Belgium

†Development Strategy and Governance Division, International Food Policy Research Institute, United States

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 fact that quality of agricultural inputs is difficult to judge, several studies note that there is considerable heterogeneity in the quality inputs on the market. For instance, in Uganda, Bold et al. (2017) tested agricultural inputs purchased in local markets, and found that 30% of nutrient is missing in fertilizer, and hybrid maize seed is estimated to contain less than 50% authentic seeds. Also in Uganda, Ashour et al. (2019) tested herbicides and found that the average bottle in their sample was missing 15% of the active ingredient and 31% of samples contain less than 75% 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 the 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 mostly populated by women continue to account for the majority of expenditure on fresh produce in many countries (Gorton et al., 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. 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. 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 good 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 will generally have 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 favorable than agro-input shops managed by a woman. The difference in rating 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 a woman. As the differences in ratings can not be immediately 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. The next section provides the context for the study and describes the main economic actors: agro-input dealers and smallholder maize farmers. We then describe how we measure perceptions, a 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.

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 varieties of contexts, usually when one or more persons are asked to assess the performance 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 of 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 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. Labour markets and hiring decisions involve situations where managers make decisions based on limited information. Discrimination in labour markets, including discrimination related to gender, has been documented in several studies. Wu (2020) uses data from an online forum for economics called "Economic Job Market Rumors" to measures gender bias in discussions about women versus men. Gender equity bias is also often studied in the context of the wage gap, whereby women appear to make substantially less money for the same work as their male counterparts. Often, this is also tied to gender equity bias in performance appraisals, when (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 used 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 et al. (2021) find that financial advisor's gender is one of the most important factors influencing a consumer's decision when choosing an 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.

The reason why gender bias features so prominently in areas such as scholarly peer review, teaching assessments or labour markets is partly due to the fact that perceptions are made explicit in the process, for instance through review reports, student feedback or hiring committees. However, in economic transactions, gender bias in perceptions remains hidden as perceptions are never measured and differences in outcomes is attributed to various other causes, such as differences in education levels between men and women.

Study context

Our study area comprises of 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 are then grouped in catchment areas. In some catchment 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 quite some heterogeneity in the 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 receives about 40 customers a day, half of which come there to buy maize seed and has been in operation for about 6 years. The shop has on average about 3 maize seed varieties in stock.

The average farmer in our sample is small, with about 3.3 acres of land for crop production. Half of our sample 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 the seed from an agro-input shop. However, use of fertilizer 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 sold at the agro-input shop is counterfeit.

Measuring perceptions

Central to our analysis is the quantification of the perceptions of the quality of services provided by agro-input dealers and of the products they sell—improved maize seed varieties in particular. 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 rank 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 agro-input dealer). We also compute an average of these six dealer level ratings. Mind that for these indicators, farmers were asked to rate the shop as a whole, which also includes the person who operates the shop.[1]

To measure the (perceived) quality of seed, farmers were asked to rate the maize seed that dealers sell on a scale of 1 to 5 on its general quality, yield, drought tolerance, pest/disease tolerance, crop duration/maturation period, and

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

germination reliability.[2] We also compute an average of these six seed level ratings. Note that 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 time in January 2022. The average farmer in our data-set provided ratings for about two agro-input dealers, with some farmers rating up to 15 agro-input dealers. The average agro-input shop received ratings from almost 12 farmers, while one agro-input shop got ratings from almost 50 farmers.

Empirical strategy

Our empirical strategy exploits the particular nature of the data, where each farmer in our dataset rates several input dealers (and each input dealer is rated by several farmers). A useful starting point is the following specification:[3]

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

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 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 can not assume that the ratings $y_{f,d}$ in equation 1 are independent. For example, the ratings that a farmer gives may be affected by a (potentially unobservable) characteristic of the farmer (eg. a poor experience with an agro-input dealer in a previous year), which may affect the ratings received by all agro-input dealers that were rate 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 my be affected by a (potentially unobservable) characteristic of the agro-input dealer (eg. dealer effort), which may affect the ratings given by all farmers that rated this particular agro-input 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 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 dyadic nature of our data leads to two-way clustering in the error term. As long as the error term is uncorrelated with the explana-

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

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

tory 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 of no effect. 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).

A useful starting point to test for an agro-input dealer gender effect is to simply compare average ratings received by male managed 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 input-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 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 to the independent variable g_d. This would be the case if, for example, female agro-input shop managers are on average lower educated than male agro-input shop managers, and lower 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 agro-input dealers. Similarly, for perceptions related to the quality of seed sold, we are particularly interested in testing if the coefficient on the gender of the input dealer changes after adjusting for various observable input 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 that are better educated generally provide higher ratings. At the same time, it may be that farmers that are higher educated are more inclined to shop at male owned 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 which 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 fixed effects model that, in addition for 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 6, which leads to:

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

Results

Table 1 reports differences on 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 of the agro-input dealers. 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. Heremale managed agro-input shops receive an average score of almost 4 out of five, while female dealers get 3.792. Interestingly, female managed agro-input shops are not rated significantly worse when asked about the quality of seed sold. They also appear to be equally rated with respect to location.

Table 1: Between dealers model focusing on dealer ratings (control variables not included, Q1).

	Dependent variable: Average of all the ratings received by dealers						
	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 2: Between dealers model focusing on seed ratings (control variables not included, Q1).

	Dependent variable: Average of all the ratings received by dealers						
	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 ().

Table 2 repeats the between input dealer analysis, but now compares ratings for seed quality attributes sold by the agro-input 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 also that the results are consistent with what was found in table 1, where we also failed to find a significant difference when asked about seed quality. This may suggest that when farmers are asked to think about a particular product, farmers make abstraction of the person selling it and the gender effect becomes less important.

Results of between agro-input dealer regressions with added control variables (see equation 5) are in Table 3 for the more general ratings of dealer characteristics and Table 4 for ratings directly related to seed quality. In all regressions, we add dealer age and dealer education level as general control variables, and add additional controls depending on the attribute being rated.

In the first column of Table 3 we start again by explaining overall dealer rating. As this is an average of all the other attributes, we also included most controls in this regression, nine in addition to dealers age and education. The reason why each control is included is provided below where we discuss 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 agro-input shops are still rated significantly higher by consumers.

The second column of Table 3 corresponds to the second column in Table 1 that compares average general 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 score based for the agro-input dealer they collected data on. Second, we construct an index that measures dealer effort and a range of services that dealers offer to clients.[4] In particular, the index includes 1) if agro-input dealers always explain how the seed should be used (seed spacing, seed rate, complementary inputs); 2) if agro-input dealer always recommend complementary inputs such as fertilizer and chemicals; 3) if agro-input dealers provide extension/training to their clients on how to use improved seed varieties; 4) if agro-input dealers provide discounts to clients that buy large quantities of maize seed; 5) if agro-input dealers sell small quantities; 6) if agro-input dealers provide seed on credit; 7) if agro-input dealers received a complaint from a customer that seed you sold was not good; 8) if mobile money was accepted as a payment modality. 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 included 1) if the roof is leak-proof; 2) if the roof is insulated to keep heat out; 3) if the walls are insulated to keep the heat out; 4) if the area where s eed is stored is properly ventilated; 5) if any official certificates are on display in the shop (e.g. inspection certificates, training certificates, registration with association, etc). We see that after controlling for these three control variables, the male premium on general ratings increase from 0.13 to 0.16. Note that the index of capital intensive seed handling and storage practices observed by the enumerator is significant has the expected sign, as input dealers that score better on the index also received higher scores on general dealership quality.[5]

When farmers are asked to assess agro-input dealers in terms of their location, the average distance[6] between the agro-input dealer and their customers

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

[5]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).

[6]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 input dealer shops and inserted as paired values in the haversine formula. This formula then calulates the distances between these paired latitudes and longitudes in metres, following which we obtain the distances in kilometres and standardize the variable.

(based on GPS coordinates), capturing some indication of centrality of the agro-input dealer, provides an obvious candidate as a control variable (third column in Table 3). We did not find a gender equity effect on ratings concerning location in Table 1 and we also do not find a difference after controlling for centrality. Note that also here, the control variable is significant in the expected direction, as dealers where the average distance between input dealer and customer is higher (or centrality is lower) also seem to be scored lower in terms of location.

In the fourth column of Table 3 we look at price competitiveness again. To account for the fact that the difference in price competitiveness ratings between male and female managed agro-input shops is driven by actual price differences between male and female managed agro-input shops, we control for average price charged by the dealer, as well as for the cost at which agro-input dealers obtain seed (which is an important determinant of the price). The analysis confirms that there is indeed a difference in perception between male and female farmers, and that this difference is not due to actual price differences. The gender equity effect is similar in size than the one found without controlling for actual price differences in Table 1. Note again that one of the control variables is significant and suggests that dealers that charge higher prices also receive significantly lower price competitiveness ratings.

The fifth column in Table 3 adds another index, this time of all seed handling and storage practices observed by the enumerator. This index includes the components of the five capital intensive seed handling and storage practices mentioned above, but also adds that 1) the agro-dealer destroys seed that exceeded shelf-life; 2) the agro-dealer stores seed in a dedicated area, away from other merchandise; 3) the agro-input dealer has not problem with rats, insects or other infestations; 4) the agro-input dealer stores seed in ambient light conditions as recomended; 5) the agro-input dealer stores seed on pallets or shelves; 6) the enumerator does not see maize seed that is stored in open bags or open containers. The index also includes the overall rating that is provided by the enumerator. As in column 5 of Table 1, we do not find a gender equity effect on seed quality rating after controlling for observable quality indicators.

In the sixth column, we repeat the analysis for perceptions related to dealers' stock, but now controlling for the number of hybrid maize varieties that the dealer has in stock and average quantity bought from the seed producers or wholesalers by the dealer (kg), the former being significant and having the expected sign. The male premium on the rating persists, although the effect did become slightly weaker as compared to a regression without controls (column 6 in Table 1)

In the seventh column we repeat the analysis for reputation, now controlling for number of years the shop has been in business, and whether the shop is registered with Uganda National Agro-input Dealer Association (UNADA), both of which we expect a direct impact on the dealer's reputation. Also here, we see that male dealers keep receiving higher scores conditional on experience and registration with UNADA, with the effect becoming slightly weaker (as compared to column 7 in Table 1).

Table 4 repeats the between input dealer analysis for seed quality attributes

Table 3: Between dealers model focusing on dealer ratings (control variables included, Q1).

	Dependent variable: Average of all the ratings received by dealers						
	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	3.785	3.77	3.829	3.34	3.822	3.647	3.921
	(0.135)	(0.227)	(0.196)	(0.167)	(0.15)	(0.204)	(0.156)
Dealer is male	0.16^{**}	0.161^{**}	-0.068	0.212^{**}	0.057	0.183^{*}	0.158^{*}
	(0.063)	(0.071)	(0.106)	(0.09)	(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	0.114	0.144	-0.056	-0.011	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	0.181^{*}	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 dealer	-0.071^{*}		-0.242^{***}				
	(0.041)		(0.064)				
Standardized sales price of maize seed	-0.099^{*}			-0.169^{**}			
	(0.051)			(0.072)			
Standardized cost of maize seed for dealer	0.079			0.071			
	(0.048)			(0.068)			
Index of all seed handling/storage practices observed by enumerator	0.096				0.184		
	(0.102)				(0.118)		
Number of hybrid maize varieties in stock	-0.034					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						0.002
	(0.006)						(0.007)
Shop's UNADA registration	0.12						0.113
	(0.096)						(0.103)
Number of obs.	150	151	152	152	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 4: Between dealers model focusing on seed ratings (control variables included, Q1).

	Dependent variable: Average of all the ratings received by dealers						
	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 ().

sold by the agro-input dealers reported in Table 2, but now we also added controls for quality related aspects of seed. As all the ratings in Table 2 concern quality, we include the same controls in all regressions. In particular,, we use the most elaborate index of all seed alding and storage practices as observed by the enumerator that was also used in model (5) of Table 3. Recall from Table 2 that we did not find a gender equity effect for any of seed quality related dimensions we look at; adding the index to control for quality does not change this. Note that the index is generally positively correlated to the rating, but only significantly so when a farmers is asked to assess the seed's yield.

Overall, comparing Table 3 to 1 and Table 2 to 4, we notice that results, both in terms of parameter estimates for β and its significance, are very similar. This suggests that difference between male and female managed agro-input shops reflects structural differences in perception between the two sexes, rather than actual differences in the dimension being rated (quality, price competitiveness, stocks and reputation).

Tables 5 and 6 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).[7] In Table 5, we use the general agro-input dealer ratings as outcome variables, similar to Table 1. 6 estimates the same model, but now for the more specific seed quality related ratings, similar to Table 2.

Table 5 shows that male managed agro-input outlets receive significantly

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

Table 5: Farmer fixed effects model focusing on dealer ratings (control variables not included, Q1).

	Dependent variable: Ratings given by the farmers						
	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 ()).

higher ratings in the areas of price competitiveness, reputation, quality in general, and stock. The average dealer rating index also shows a significant difference between male and female dealers. Comparing Table 5 to Table 1, 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 6 to 2, we see that, after controlling for farmer level heterogeneity, some of the differences in seed quality related ratings between male and female dealers turned significant. For perceptions related to seed germination, male managed agro-input shops receive a rating score that is on average 0.11 higher than the seed germination rating female managed agro-input shops receive. We further find signs of gender equity 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 index between male and female managed agro-input shops (column 1).

The fact that we also find gender equity bias when farmers are asked to assess seed quality after controlling for farmer fixed effect suggests that, in the between regressions of Tables 2 and 4, gender equity bias is obscured by farmer level confounders. For instance, it could be that farmers that are higher educated also provide higher rankings and that these higher educated farmers are also more likely to shop at female owned 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 ran fixed effects model that, in addition for controlling for farmer heterogeneity, also controls for dealer level observable characteristics (see equation 8), similar to Tables 3 and 4. Results are in Table 7 for the more general input dealer ratings, and Table 8 for seed quality ratings.

We find that controlling for dealer level observable characteristics does not change findings for the first set of rating that evaluate the agro-input dealer.

Table 6: Farmer fixed effects model focusing on seed ratings (no controls included, Q1).

	Dependent variable: Ratings given by the farmers						
	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 ()).

Largest gender equity effects are found when farmers are asked to rate agro-input dealer reputation (column 7) and price competitiveness (column 7); in both cases male managed agro-input shops are rated about .2 points higher. Differences in rating between male and female managed agro-input shops for the stock attribute has become indistinguishable from zero.

Comparing Table 6 and Table 8, the significant difference between male and female managed agro-input shops with respect to seed maturity rating (column 6), germination (column 7), and overall seed quality ratings (column 2) found in Table persist after controlling for observable dealer level differences in seed quality.

Conclusion and Policy Implications

Using survey data from smallholder farmers and agro-input dealers in southeastern Uganda, we tested if farmers perceived 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 (very good). Not only did we ask farmers to rate agro-input dealers on a set of general characteristics such as accessibility and price competitiveness, we also asked farmer to focus on a particular product that these agro-input dealers sold (maize seed), and to rate this product on various dimensions like germination, yield, etc.

Using simple agro-input dealer comparisons of average ratings given to male and female managed agro-input shops, we found that female managed agro-input shops were generally rated lower than their male 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 between male and female managed agro-input shops reflect structural differences in perception between the two sexes rather than actual

Table 7: Farmer fixed effects model focusing on dealer ratings (control variables included, Q1).

	Dependent variable: Ratings given by the farmers						
	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	0.114^{***}	0.149^{**}	0.026	0.199^{***}	0.03	0.082	0.201^{***}
	(0.034)	(0.058)	(0.049)	(0.049)	(0.047)	(0.051)	(0.048)
Dealer's age in years	0.002^{**}	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 education	0.009	0.043	0.029	−0.03	0.037	−0.007	−0.003
	(0.024)	(0.036)	(0.035)	(0.035)	(0.037)	(0.036)	(0.032)
Shop's cleanness/professionality rating by enumerator		0.021					
		(0.015)					
Index of dealer's efforts and services	0.011	−0.004					
	(0.028)	(0.043)					
Index of capital-intensive seed handling/storage practices observed by enumerator		0.057^{*}					
		(0.031)					
Standardized distance between farmer and dealer	0.005		0.004				
	(0.01)		(0.014)				
Standardized sales price of maize seed	-0.021^{*}			0.005			
	(0.012)			(0.019)			
Standardized cost of maize seed for dealer	0.016			−0.003			
	(0.013)			(0.019)			
Index of all seed handling/storage practices observed by enumerator	−0.006				0.072^{*}		
	(0.023)				(0.04)		
Number of hybrid maize varieties in stock	−0.006					0.001	
	(0.008)					(0.011)	
Standardized amount of maize seed dealer bought	−0.002					0.013	
	(0.008)					(0.013)	
Number of years since shop's establishment	0.006^{***}						0.015^{***}
	(0.002)						(0.003)
Shop's UNADA registration	−0.018						0.002
	(0.025)						(0.031)
Number of obs.	2824	3014	3433	3347	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 8: Farmer fixed effects model focusing on seed ratings (control variables included, Q1).

	Dependent variable: Ratings given by the farmers						
	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 ()).

differences.

However, ratings of agro-input dealers provided by the farmer 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 gender, and ran farmer fixed effects models. 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 dimension of seed quality sold by agro-input dealers of different gender.

Looking into the different dimensions that were rated, we found 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 found male managed agro-input shops to have significantly better reputation than female dealers. This reputation difference was also reflected in a significant difference between male and female dealers when directly asked about overall general quality. On the other hand, we did 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 seed itself, gender equity bias was largest when farmers were asked to assess seed germination rates and whether the seed being rated had the maturing period as advertised.

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 solemnly on increasing women empowerment are unlikely to be sufficient, and may in some cases even backfire. It will be important to challenge gender stereotypes and role congruence and such interventions should not only focus on one gender.

Gender norms and customs prevent women from aspiring and developing an internal locus of control. 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 Disney feel good 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 et al., 2012).

Gender roles and customs also prevent women from realizing their full potential indirectly, as men do not support (or even prevent participation 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 case this perception is inaccurate, simply correcting this perception may be effective. For example, Bursztyn et al. (2020) find that in Saudi Arabia, a country with strict norms and traditions on mobility of women, many men overestimate the degree of peer judgment if their wives work outside of the house. Correcting this false perception lead to a significant increase in women employment. Also here, role models can be important to challenge beliefs and stereotypes about lesser abilities of another group held by other groups: Beaman et al. (2009) show that the appointment of women leaders to Indian village councils improved men's perceptions of women's leadership abilities.

Apart from underscoring the importance of gender norms and customs in shaping perceptions, our study also 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 depends on many attributes of the program. This include the more obvious things 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 make training attendance publicly visible, perhaps through a register of trained agro-input dealers, through certificates that are advertised in the shops etc, such that equal ability between male and female managed agro-input shops becomes more salient to clients.

Second, the share of women among opinion leaders and experts in the sector also 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 the Uganda National Agro-input Dealer Association (UNADA) needs to increase. For public sector positions, quota's may be considered.

Finally, we found that biased perception exist especially with respect to prices charged by agro-input dealers. Also here, simply advertising prices may be sufficient to make prices objectively verifiable, and customers need to depend less on perceptions and use 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 contained here is the sole responsibility of the authors, and does not reflect the views of any funding agency or organization mentioned here.

References

Anderson, M. L. (2008). Multiple inference and gender differences in the effects of early intervention: A reevaluation of the abecedarian, perry preschool, and early training projects. *Journal of the American statistical Association 103*(484), 1481–1495.

Ashour, M., D. O. Gilligan, J. B. Hoel, and N. I. Karachiwalla (2019). Do beliefs about herbicide quality correspond with actual quality in local markets? evidence from uganda. *The Journal of Development Studies 55*(6), 1285–1306.

Barriga, A. and N. Fiala (2020). The supply chain for seed in uganda: Where does it go wrong? *World Development 130*, 104928.

Beaman, L., R. Chattopadhyay, E. Duflo, R. Pande, and P. Topalova (2009). Powerful women: does exposure reduce bias? *The Quarterly journal of economics 124*(4), 1497–1540.

Bold, T., K. C. Kaizzi, J. Svensson, and D. Yanagizawa-Drott (2017, 03). Lemon Technologies and Adoption: Measurement, Theory and Evidence from Agricultural Markets in Uganda*. *The Quarterly Journal of Economics 132*(3), 1055–1100.

Bursztyn, L., A. L. González, and D. Yanagizawa-Drott (2020, October). Misperceived social norms: Women working outside the home in saudi arabia. *American Economic Review 110*(10), 2997–3029.

Cameron, A. C. and D. L. Miller (2015). A practitioner's guide to cluster-robust inference. *Journal of human resources 50*(2), 317–372.

Card, D., S. DellaVigna, P. Funk, and N. Iriberri (2019, 11). Are Referees and Editors in Economics Gender Neutral?*. *The Quarterly Journal of Economics 135*(1), 269–327.

Chari, A. and P. Goldsmith-Pinkham (2017). Gender representation in economics across topics and time: Evidence from the nber summer institute. Technical report, National Bureau of Economic Research.

Correll, S. J., K. R. Weisshaar, A. T. Wynn, and J. D. Wehner (2020). Inside the black box of organizational life: The gendered language of performance assessment. *American Sociological Review 85*(6), 1022–1050.

Giroux, S., J. Blekking, K. Waldman, D. Resnick, and D. Fobi (2021). Informal vendors and food systems planning in an emerging african city. *Food Policy 103*, 101997. Urban food policies for a sustainable and just future.

Gorton, M., J. Sauer, and P. Supatpongkul (2011). Wet markets, supermarkets and the "big middle" for food retailing in developing countries: Evidence from thailand. *World Development 39*(9), 1624–1637.

Hospido, L. and C. Sanz (2021). Gender gaps in the evaluation of research: Evidence from submissions to economics conferences*. *Oxford Bulletin of Economics and Statistics 83*(3), 590–618.

Hünermund, P. and B. Louw (2020). On the nuisance of control variables in regression analysis. *arXiv preprint arXiv:2005.10314*.

Kahneman, D. (2017). Thinking, fast and slow.

Klein, G., Z. Shtudiner, and M. Zwilling (2021). Uncovering gender bias in attitudes towards financial advisors. *Journal of Economic Behavior & Organization 189*, 257–273.

La Ferrara, E., A. Chong, and S. Duryea (2012, July). Soap operas and fertility: Evidence from brazil. *American Economic Journal: Applied Economics 4*(4), 1–31.

Le Barbanchon, T. and J. Sauvagnat (2021, 07). Electoral Competition, Voter Bias, and Women in Politics. *Journal of the European Economic Association 20*(1), 352–394.

Mitchell, K. M. and J. Martin (2018). Gender bias in student evaluations. *PS: Political Science & Politics 51*(3), 648–652.

Pair, E., N. Vicas, A. M. Weber, V. Meausoone, J. Zou, A. Njuguna, and G. L. Darmstadt (2021). Quantification of gender bias and sentiment toward political leaders over 20 years of kenyan news using natural language processing. *Frontiers in Psychology 12*.

Porter, C. and D. Serra (2020, July). Gender differences in the choice of major: The importance of female role models. *American Economic Journal: Applied Economics 12*(3), 226–54.

Riley, E. (2022, 01). Role Models in Movies: The Impact of Queen of Katwe on Students' Educational Attainment. *The Review of Economics and Statistics*, 1–48.

Wu, A. H. (2020). Gender bias among professionals: an identity-based interpretation. *Review of Economics and Statistics 102*(5), 867–880.