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Short communication

The seeds of misallocation: Fertilizer use and maize varietal misidentification in Ethiopia☆

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ABSTRACT

Optimal input allocation in agriculture leverages production complementarities. For example, improved seeds are generally more responsive to fertilizer than traditional seeds. Thus, inaccurate beliefs about whether seeds are improved may result in sub-optimal fertilizer application. We document precisely this pattern using data from Ethiopia that allows us to compare farmer beliefs about their maize seeds with genotyping data that identify the true genetics of these seeds. We find that 15 percent of farmers believe incorrectly that they are using improved varieties and use far more fertilizer than farmers who correctly believe that they sowed traditional varieties. Conversely, we find that about 15 percent of farmers believe incorrectly that they are growing traditional material and use far less fertilizer than those farmers who correctly believe that they are growing improved material. We extrapolate from our nationally representative sample to estimate the national-level magnitude of fertilizer misallocation due to incorrect seed beliefs.

1. Introduction

The Green Revolution was sparked by innovations in plant breeding and fueled by complementarities between improved seeds and other inputs. Improved crop genetics were strongly complementary with inputs of chemical fertilizers and irrigation; in many contexts, they also complemented agricultural labor. Realizing the potential yield gains of better crop germplasm requires careful adjustment of other applied inputs (Foster and Rosenzweig, 1995). Hybrid maize, for example, can produce dramatically higher yields than traditional varieties when optimally fertilized, but deviations from the optimum can rapidly reduce the economic returns (Duflo et al., 2008).

In the presence of such complementarities, farmers must know what seeds they have sown in order to know how best to manage their crops. Inaccurate information or beliefs about the seed type can impose direct or indirect costs on farmers via sub-optimal input applications and lower returns. Most obviously, farmers who erroneously believe that they are growing improved seeds may purchase costly inputs in anticipation of high returns that are eventually unrealized. Conversely, farmers who incorrectly believe that they are growing unimproved (traditional) crop varieties may decline to purchase and apply inputs that could increase on-farm profits. In both cases, farmers' incorrect beliefs about the genetics of their seeds will lead to static inefficiencies in the application of inputs. These losses relative to optimal input use, which are likely asymmetric, are depicted in a conceptual model in the Appendix. Such input distortions are potentially important for fertilizer applied to maize, the focus of this study: while increased nitrogen use will, to a point, increase yield of both traditional and improved maize varieties, on the margin improved varieties tend to be more nitrogen-responsive. Beyond static losses, incorrect beliefs may also impose dynamic costs by undermining farmers' ability to learn about and adopt profitable technologies. Farmers may conclude that improved seeds and fertilizer represent poor investments, for instance, if they incorrectly believe that they have been using both but have experienced low or negative returns (Bold et al., 2017). More generally, farmers are trying to draw inferences about the mapping from inputs and management practices to profits, and this mapping can be badly scrambled by inaccuracies in farmers' information sets (Patel, 2024).

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We draw on new data from Ethiopia in which we are able to compare farmer-reported seed types to the true genetic identity of their seed.[1] Ethiopia provides an interesting context for this study because improved maize seeds and chemical fertilizers have diffused widely across the country since the 1990s, in response to government programs, extension encouragement and specific fertilizer recommendations (Spielman et al., 2013; Abate et al., 2015; Kosmowski et al., 2020). Official recommendations specifically encourage maize farmers to use nitrogen fertilizers and implicitly reflect input complementarities by recommending more nitrogen for hybrid (improved) maize than for non-hybrid maize (Abate et al., 2015). However, the Ethiopian context is also characterized by limited seed system regulation as well as widespread practices of seed saving and informal farmer seed exchange. These features all work to introduce substantial on-farm uncertainty about the genetic makeup of the seeds farmers sow.

We find that (i) nearly one-third of Ethiopian maize farmers hold false beliefs about the types of seeds that they are growing; (ii) those who falsely believe they sowed improved seed apply far more nitrogen fertilizer than farmers who correctly believe they sowed traditional seed, adding an average of $84 (20 days wages) or more to their per hectare expenditure on purchased inputs; and (iii) those who falsely believe that they are growing traditional seeds use half or less the level of fertilizer chosen by farmers who correctly understand that their seeds are improved. The overall implication is that significant quantities of fertilizer are likely to be inefficiently allocated, with policy implications for seed systems and management of agricultural input supply chains.[2] We conduct a scaling exercise to project fertilizer overuse and underuse at the national level; the results suggest that around 20,000–30,000 mt of nitrogen would be allocated differently if maize farmers had correct beliefs about their seeds, an amount corresponding to roughly 4%–6% of Ethiopia's total nitrogen use.[3]

We join previous researchers in highlighting that mistaken seed beliefs also pose a problem for researchers as a troubling source of non-classical measurement error (Abay, 2020; Abay et al., 2021, 2023, 2019). Out of necessity, the agricultural technology adoption literature has historically relied exclusively on farmer self-reports about improved seed use and on the (often problematic) assumption that new varieties are readily distinguishable from older ones (Macours, 2019). Genotyping advances now offer a compelling alternative. Samples taken from farmers' fields can be DNA fingerprinted as a means of objective seed varietal identification (Stevenson et al., 2018; Beegle et al., 2012). This measurement innovation has enabled a number of empirical studies that document how varietal types (e.g., improved or not) and names are commonly misperceived by farmers, introducing measurement error in data based on self-reports. We build on this emerging literature, which finds – across a variety of contexts and crops – that substantial fractions of farmers hold false seed beliefs (Wineman et al., 2020; Maredia et al., 2016; Floro et al., 2018; Yirga et al., 2016). Wossen et al. (2022) provide evidence that seed misclassification is due to misperception (i.e., false beliefs) rather than intentionally misleading misreporting, which we also assume throughout our analysis.

The link we test between seed beliefs and fertilizer use hinges on the fact that improved seeds are generally more responsive to chemical fertilizer than seeds of lower genetic quality (Ellis, 1992; Tolessa et al., 2001; Nyangena et al., 2014; Kassie et al., 2015).[4] Farmers are well aware of the complementarity between improved seed and chemical fertilizer, and official fertilizer recommendations are typically higher for improved varieties. In our context, Abay et al. (2018) show that improved maize seeds and fertilizer are strong production complements and that Ethiopian farmers understand this interaction and manage their maize production accordingly.

Our paper builds on two related sets of published studies. The first set consists of a pair of "double blind" studies in Tanzania (Bulte et al., 2014, 2023), in which researchers distributed improved and traditional seeds to farmers. Only a subset of farmers were told which seeds they had received. All other farmers only knew that there was a 50/50 chance the seeds were improved. Bulte et al. (2014) conduct this study with cowpea seeds and found that farmers who knew for certain – and also those who understood that there was a 50/50 chance they were sowing improved seeds – were more attentive, exerted greater effort and, consequently, produced higher yields, even if they were in fact growing a traditional variety. Farmers who knew they were sowing traditional seeds produced significantly lower yields. In the follow-on study, Bulte et al. (2023) conducted a similar study with maize seeds. In the face of uncertainty about the type of seeds they were sowing, farmers reduced labor investments and thereby produced lower yields. In this context, however, improved maize seeds were sufficiently superior to traditional seeds that yields were higher with the improved seeds despite these reduced labor investments – albeit lower than when farmers knew they were sowing improved seeds and could optimize their labor allocation accordingly.

In contrast to these two studies, we leverage the natural prevalence of false seed beliefs among farmers, rather than artificially manipulating these beliefs. Because we can measure directly the extent of false beliefs in a nationally-representative sample of farmers, we can show that this is a quantitatively important problem. Moreover, while the lack of pure experimental variation in information complicates causal identification, we are able to observe the choices that farmers make in real-world settings, strengthening the external validity of our study.

The second set of studies that we build on includes two closely related papers that address different contexts, where the issues raised are of lower salience or where data constraints limit the external validity of the analysis. Wossen et al. (2022) use DNA fingerprinting data from Nigerian cassava farms to demonstrate how farmer misperceptions of varietal quality distort on-farm applications of fertilizer and herbicide. We use a similar approach to test for distorted input applications in the context of maize in Ethiopia. The change of case and context is important. Maize is a more input-intensive crop than cassava; in many contexts in sub-Saharan Africa, fertilizer use on cassava tends to be much lower than for maize.[5] In our context, most farmers are well aware of the differential returns that are expected to fertilizer applications on improved and traditional maize seed.

Our paper is also related to work by Wineman et al. (2020), who use a simple comparison of mean input usage between farmers with correct and incorrect beliefs about the maize seeds they sowed, in the context of Tanzania. Farmers who self-report growing an improved variety use more fertilizer compared to those who do not. Because this survey, which is not nationally representative, was constructed specifically to focus on narrow questions of varietal identification and input use, the

[1] For a detailed discussion of this dataset and the novel insights it enables related to technology adoption, see Kosmowski et al. (2020).

[2] To be clear, we cannot be confident which farmers are overusing fertilizer and which farmers are underusing it. Indeed, given the low rates of fertilizer use, it is possible that *all* farmers are underusing fertilizer. However, there is clearly some static inefficiency here. There will certainly also be confusion for farmers trying to assess the profitability of other inputs and practices.

[3] Based on FAOSTAT estimates of total agricultural use of nutrient nitrogen. (Accessed 30 April 2024).

[4] This differential responsiveness for improved germplasm is often intentionally part of the breeding process, but it may also arise as an artefact of the plant breeding process, since breeders often select improved varieties based on their performance under growing conditions characterized by high levels of input use.

[5] As one recent review article put it, "In general, fertilizer use on roots and tuber crops in Sub-Saharan Africa is negligible" (Ezui et al., 2016). However, the Cassava Monitoring Survey on which Wossen et al. (2022) draw focuses on a purposively constructed sampling frame in Nigeria. In this sample, fertilizer use on cassava is both widespread and sizeable.

data include relatively few variables to control for relevant farmer and community characteristics.

In contrast, our data allow us to consider the same issues in the context of a nationally representative sample and a broad household survey that includes a rich set of household and community characteristics. This is important, because false belief about seed types is not randomly assigned, outside the experimental settings of Bulte et al. (2014, 2023). Our data allow us to control for a broader set of observables than either Wossen et al. (2022) or Wineman et al. (2020). This allows us to address selection on observables. The structure of our data also allows us then to extrapolate the results of our analysis to produce national-level estimates of varietal misidentification and input use.

Our analysis does not allow us to identify *why* farmers may hold false seed beliefs. Some of the related literature has suggested that there is widespread counterfeiting or adulteration of inputs at some point in the supply chain (e.g., Bold et al., 2017). While this is possible, other explanations are also plausible. Farmers may simply not be aware of the characteristics of improved varieties (Kosmowski et al., 2019; Maredia et al., 2016). In our context, farmer-saved maize seeds tend to lose their genetic purity over time (Ilukor et al., 2017). This particularly affects hybrid seeds, but to some degree also holds for a type of non-hybrid improved maize, known as open-pollinated varieties (OPVs), that have been widely distributed through markets and government programs. Farmers who purchase hybrid seed in one season and save the seed for replanting in following years will very quickly (or more slowly, with OPVs) end up with seeds that are genetically unlike the original improved variety, but they may continue to view the seeds as improved. Farmers may also have purchased or been given seed that they understood, incorrectly, to be improved. Somewhat more surprising are those farmers – reasonably numerous in our data – who are growing improved seed without realizing it. These farmers may be growing OPVs, which maintain their genetic purity fairly well over time. Farmers may assume that since they have not recently purchased seed, the genetic quality is unimproved. In this paper, we cannot explain the reasons for misidentification, although we identify a number of correlates.

2. Data

We use data from the fourth wave of the Ethiopian Socioeconomic Survey (ESS4) to investigate the effects of seed misclassification on input allocation. This survey uses a two-stage sample that is nationally representative.[6] The ESS collects household data related to agricultural production and includes detailed questions at the plot, household, and community levels. In addition to eliciting detailed reports of fertilizer usage, the 2018/19 round selected a sub-sample of maize-producing households in Ethiopia's major maize-growing regions. For most of these households, one maize plot was selected for further analysis.[7] The survey team visited the plot at harvest time and conducted a crop cut to objectively measure the maize yield. This produced a total sample of 506 fields, randomly selected at the level of the enumeration area (EA).[8] Maize samples from these crop cuts were then genotyped to reveal the genetic identity of the maize varieties, making the ESS4 the first nationally-representative household survey in the public domain that incorporates DNA fingerprinting for varietal identification (Kosmowski et al., 2020).

Although ESS4 includes DNA fingerprinting data for other crops, we restrict our focus to maize for several reasons. Maize is now the most commonly grown crop by smallholder farmers in Ethiopia, and maize area has seen a sharp increase over the past 20 years (Stevenson et al., 2018). Furthermore, the crop also has the highest reported adoption rate of improved seeds in Ethiopia (Mekonen et al., 2019). Evidence from observational studies (Abay et al., 2018) is consistent with on-station experiments conducted by the national research system in finding that improved maize varieties (especially maize hybrids) are more input-responsive than improved varieties of other crops.

In spite of the availability of genotyping data, defining improved varieties in a genetic sense is not conceptually straightforward. We follow common seed-industry practices in defining a collected sample to be "improved" if it matched 95% of selected genetic markers associated with the originally-released breeder seeds in a reference library.[9]

This 95% purity threshold guarantees seed uniformity and genetic proximity to the originally-released cultivar. However, we provide robustness tests to show that our main results hold qualitatively for other thresholds in the 70% to 97.5% range.[10]

We distinguish four different seed belief types, according to two binary variables. The first indicates whether the farmer reports having planted improved or traditional seeds, based on the post-planting round of the survey. The second indicates whether the genetic fingerprinting test for the post-harvest sample revealed that it is improved ("DNA Type"), based on our chosen purity threshold. When the two variables align, the farmer has correct seed beliefs. Farmers who correctly report sowing improved seeds have "True Positive" (TP) beliefs, while farmers who correctly report sowing traditional seeds have "True Negative" (TN) beliefs. When the two variables are not aligned, the farmer has false seed beliefs. Farmers who incorrectly report sowing improved seeds have "False Positive" (FP) beliefs, while those who incorrectly report sowing traditional seeds have "False Negative" (FN) beliefs. While farmers' self-reports do not change with the purity threshold discussed above, the DNA Type obviously does. In a mechanical sense, then, higher purity thresholds alter belief types. Since a higher threshold means that fewer samples are identified as "Positive" for genetic improvement, observations tend to shift from TP to FP and from FN to TN. Fig. 1 shows how the distribution of TP, FP, TN, and FN beliefs changes as the purity threshold increases from 70% to 97.5%.

We evaluate the effect of these seed beliefs on agricultural input allocation, with a specific focus on the application of purchased nitrogen fertilizer. To account for the fact that different types of fertilizer are substitutable and often used interchangeably depending on local availability, we convert all chemical fertilizer applications into total nutrient equivalents for nitrogen and phosphorus.[11] Ideally, our measure would also include nutrients applied in the form of animal manure, but we lack information on quantities of manure that are applied and on its nutrient content. As a result, we simply include a dummy variable to indicate whether farmers have applied any manure.

Fig. 2 shows cumulative distributions of the nitrogen equivalents in kg per hectare. Panel (b) of this figure shows clearly that farmer seed beliefs – combined with their apparent understanding of production complementarities between improved seeds and nitrogen – drive nitrogen applications much more strongly than the actual DNA type of the seed they sowed, shown in Panel (a). As a further disaggregation

[6] For details about the sampling frame, see https://microdata.worldbank.org/index.php/catalog/3823/download/49208 (Accessed 9 August 2023).

[7] For 13% of households, more than one plot was sampled.

[8] A lack of technical consistency between the different survey modules (with identifiers either missing or not matching) and missing or unrecoverable values for individual observations reduces the final sample to 432 observations from 112 distinct EAs (compared with 122 EAs in the full DNA subsample).

[9] See Appendix for a detailed discussion.

[10] The 70% threshold is a low match and tends to treat as "improved" some material that may not perform very differently from unimproved material.

[11] Data from http://www.soilcropandmore.info/soil/fertiliz.htm (last accessed 9 August 2023) show the nitrogen and phosphorus contents for each respective fertilizer (for Nitrogen: Urea = 46% DAP = 18% NPS = 10%; for Phosphorus: Urea = 0% DAP = 46% NPS = 42%). Although one high-profile study found that actual nitrogen content may deviate from these expected levels (Bold et al., 2017), other studies suggest that similar results may be generated by errors in testing rather than true nutrient deficiencies. See Michelson et al. (2024) or https://blogs.worldbank.org/impactevaluations/devil-details-measuring-agricultural-input-quality (Accessed 19 April 2023).

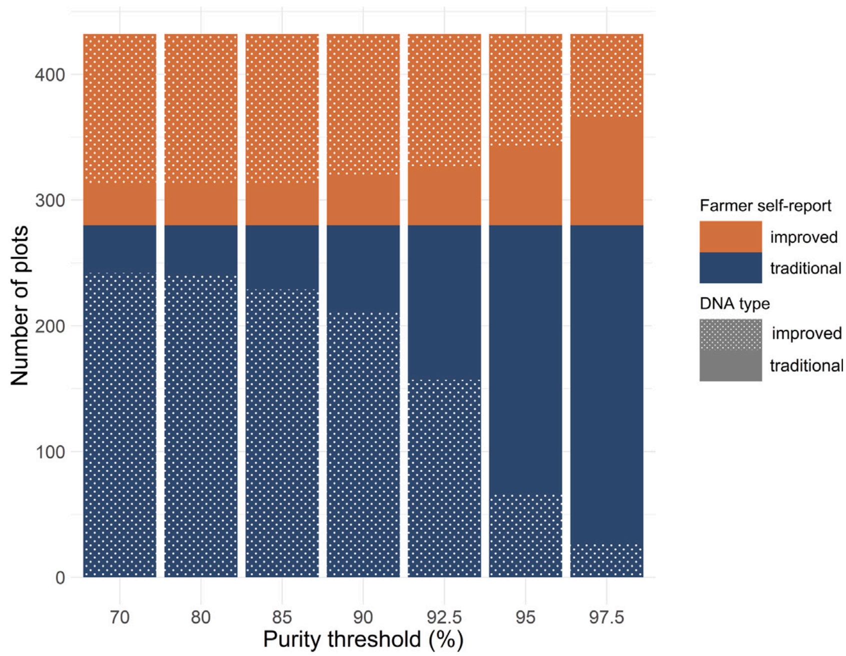

Fig. 1. Distribution of seed beliefs for improved maize varieties at the plot-level based on farmer self-reports in survey and DNA fingerprinting results for different genetic purity thresholds for distinguishing improved from traditional seeds. Color indicates the farmer belief (orange = improved, blue = traditional), and pattern denotes the DNA type (dots = improved, none = traditional). Numerical results are reported in Table A1. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

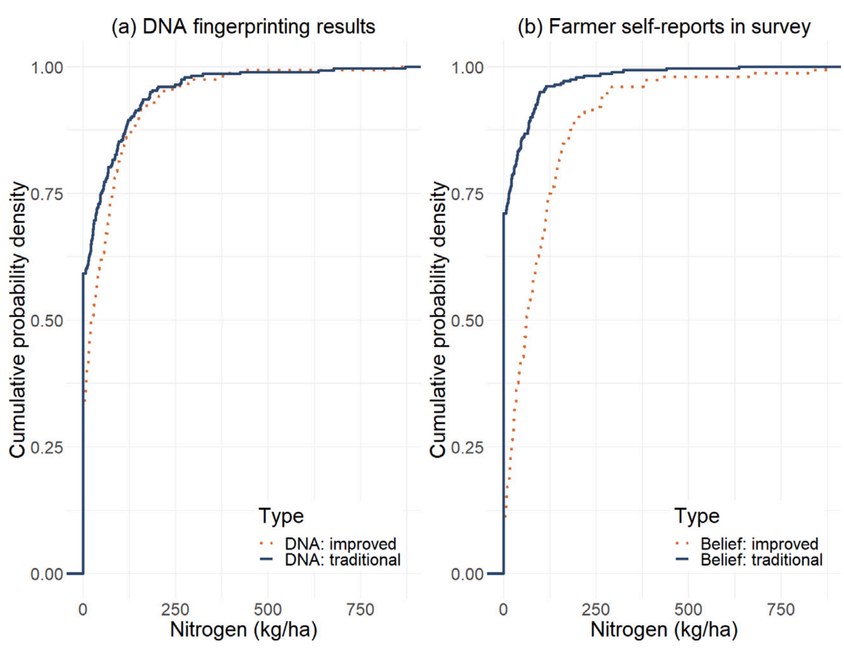

Fig. 2. Cumulative distribution of purchased fertilizer measured in nitrogen equivalents by (a) DNA type at a 95% purity threshold and (b) self-reported seed belief. Official nitrogen recommendations range from 110–130 kg/ha (higher for hybrid (improved) maize) (Abate et al., 2015).

of these nitrogen use distributions, Figure A2 shows the same figures by belief type (i.e., TP, TN, FP, FN). As a benchmark, 75% of farmers who report sowing improved maize apply less than the government recommendation of 130 kg/ha for hybrid (improved) maize; over 90% of those who believe they are growing traditional maize apply less than their slightly lower recommendation. While it is unclear how seriously farmers (should) take the nationally uniform recommendations, given that they face highly heterogeneous shadow prices and returns, a literal interpretation would imply that costly under-use is a more prevalent problem than costly over-use of nitrogen. For the median farmer of the two types in panel (b) of Fig. 2, nitrogen use is less than half this recommendation (improved) and zero (traditional). If the government recommendation were close to optimal in the context of the simple model depicted in Figure A1, this means that false positive seed beliefs may actually 'distort' nitrogen use in a way that *increases* profits for many of the farmers in our sample.

We provide descriptive statistics for general respondent-level and agricultural production variables by belief type in Table 1. In columns (5)–(10), we report differences in these variables between specified pairs of these belief types. None of the demographic variables is systematically (statistically) different by belief type, but we do see a number of clear differences in production-related characteristics. Farmers who

Table 1
Descriptive statistics by seed belief categories for demographic and production variables with pairwise differences.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	True positive (TP)	False positive (FP)	True negative (TN)	False negative (FN)	Belief = improved	DNA = Belief	DNA = improved	DNA = traditional	DNA ≠ Belief	Belief = traditional
	Means				FP vs TP	TN vs TP	FN vs TP	TN vs FP	FN vs FP	FN vs TN
General Respondent Variables										
Gender (female = 1)	0.18	0.17	0.17	0.12	−0.01	−0.01	−0.06	−0.01	−0.05	−0.05
	(0.39)	(0.38)	(0.37)	(0.33)	(0.06)	(0.05)	(0.06)	(0.05)	(0.07)	(0.05)
Age (years)	43.46	47.59	47.62	46.59	4.13	4.16	3.13	0.03	−1.00	−1.03
	(14.30)	(15.40)	(14.85)	(15.53)	(2.46)	(1.88)	(2.42)	(2.14)	(2.63)	(2.10)
Education (attended any school = 1)	0.35	0.41	0.37	0.44	0.06	0.03	0.09	−0.04	0.03	0.07
	(0.48)	(0.50)	(0.48)	(0.50)	(0.08)	(0.06)	(0.08)	(0.07)	(0.09)	(0.07)
Agricultural Production Variables										
Extension contact (yes = 1)	0.83	0.71	0.44	0.52	−0.12	−0.39***	−0.32***	−0.27***	−0.20*	0.07
	(0.38)	(0.46)	(0.50)	(0.50)	(0.08)	(0.06)	(0.08)	(0.07)	(0.08)	(0.07)
Seeds purchased (yes = 1)	0.93	0.76	0.17	0.21	−0.17**	−0.76***	−0.72***	−0.59***	−0.55***	0.04
	(0.25)	(0.43)	(0.37)	(0.41)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)
Land area (ha)	0.16	0.14	0.09	0.11	−0.02	−0.08***	−0.06**	−0.06**	−0.04	0.02
	(0.16)	(0.16)	(0.10)	(0.17)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Nitrogen (kg/ha)	77.65	127.85	19.05	35.62	50.20***	−58.60***	−42.03**	−108.79***	−92.23***	16.57
	(113.26)	(145.57)	(59.77)	(74.07)	(15.02)	(11.50)	(14.82)	(13.07)	(16.06)	(12.84)
Manure (yes = 1)	0.29	0.37	0.48	0.33	0.07	0.18**	0.04	0.11	−0.03	−0.14
	(0.46)	(0.49)	(0.50)	(0.48)	(0.08)	(0.06)	(0.08)	(0.07)	(0.09)	(0.07)

Notes: Number of observations: 432. Plots have been classified into farmer belief types based on farmer self-report and DNA type evaluated at a 95% threshold for genetic purity. Columns (1)–(4) present the mean values of the respective variables and columns (5)–(10) show the differences between these groups. Tukey tests for equality of mean values. Amounts of nitrogen are simple aggregates of the respective nitrogen contents of three fertilizers: Urea = 46%, DAP = 18%, NPS = 10%.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

reported sowing improved seeds, whether this belief is true (TP) or false (FP), are more likely to have participated in extension programs, to have purchased the seed they sowed, and to have larger total land holdings. TP and FP farmers also apply nitrogen at much higher rates on average than those with TN and FN beliefs. Farmers with TN beliefs rely more on manure as a source of fertilizer. Similar descriptive statistics for a broader set of variables (see Table A2) indicate minimal systematic differences beyond input allocation, except for FP farmers, who exhibit higher access to credit and are situated in less remote areas.

3. Empirical strategy

In this section, we first present the econometric specifications that we use to estimate the impact of seed beliefs on input allocations. We discuss issues related to causal identification and related concerns. We then present a prediction exercise that allows us to project the observed on-farm effects onto data covering the entirety of Ethiopia to arrive at national-level estimates of seed misclassification and fertilizer use.

3.1. Seed beliefs and on-farm input allocation

We are interested in estimating the effects of farmer seed beliefs on their on-farm investment of other inputs. We focus specifically on nitrogen fertilizer application, as the most important and most common purchased input in this context. We estimate the same specification for other purchased inputs and present results in the Appendix.

In contrast to experimental approaches that artificially manipulate farmers' seed beliefs (e.g., Bulte et al., 2014, 2023), we rely on observational data. It is difficult to imagine any defensible instruments that could be used to isolate plausibly exogenous variation in seed beliefs (i.e., instruments that would satisfy the exclusion restriction). We therefore adopt a second-best empirical strategy that relies on a progressively richer set of controls and post-double selection (PDS) LASSO to account for potentially omitted variables (Belloni et al., 2014). This approach is possible given the detailed set of variables collected by the ESS4. We discuss below the plausibility of a causal interpretation of the results.

Our standard specification is as follows:

$$y_i = \alpha + \beta Belief_i + \gamma DNA_i + \delta Belief_i \times DNA_i + \mathbf{x}_i' \zeta + \epsilon_i, \quad (1)$$

where y_i is effective nitrogen use in kg per hectare for plot i, $Belief_i$ and DNA_i are indicator variables corresponding respectively to the farmer's belief that the seed is improved, and the DNA test results for each plot. This specification nests estimates of all four belief types – TP, FP, TN, and FN – in one model. Relative to the omitted category (TN), $(\beta+\delta)$ gives the TP effect, β alone gives the FP effect, and γ alone gives the FN effect. We include a vector of control variables, $\mathbf{x_i}$, that we expand to include progressively broader sets of controls. We estimate this specification by OLS and cluster standard errors at the EA level.

Identification of the primary effects of interest in this case requires that $Belief_i$ and DNA_i are uncorrelated with ϵ, conditional on $\mathbf{x_i}$. Given the richness of the ESS4 data, we estimate a version of this specification in which additional controls in $\mathbf{x_i}$ are chosen using PDS LASSO. We leverage the high-dimensional nature of our dataset by offering a large number and variety of candidate variables for the algorithm to choose from. Specifically, we include $Belief_i$, DNA_i and $Belief_i \times DNA_i$ as either 'treatment' variables or as part of the amelioration set.[12]

The full set of potential controls in $\mathbf{x_i}$ includes 288 variables from the post-planting, post-harvest, household and community questionnaires, as well as a set of spatial variables at the household and plot level; we also include all squared terms and pairwise interactions. We estimate a regression that includes the controls selected by PDS LASSO in addition to a predefined amelioration set. Information on the composition of the data set and selected variables is reported in Table A3.

[12] To be precise, we designate either $Belief_i$ or DNA_i to be the 'treatment' variable in the PDS LASSO. We then impose the requirement that the amelioration set must include the other variable and the interaction term $Belief_i \times DNA_i$, as well as the set of extended 'controls'. All other potential control variables are then included or excluded based on the PDS LASSO estimation (Belloni et al., 2014).

3.2. DNA prediction and projection of national nitrogen use

We aim to extend our estimates to the national level, in order to estimate the magnitude of overuse and underuse by farmers who misidentify their seeds. This exercise consists of three stages: (1) we extrapolate the results from the subsample of maize-growing households whose plots were sampled and tested to the wider ESS4 sample of maize-growing households; (2) we scale these results to estimates of observed national-level nitrogen use by belief type; and (3) we use our empirical model to estimate nitrogen use by FP and FN farmers under a counterfactual of *corrected* beliefs.

3.2.1. Predicting DNA type beyond the sampled plots

In each ESS4 EA in major maize-growing regions (such as Tigray, Amhara, Oromia, Harar, and the so-called Southern Nations, Nationalities, and People's Region), up to 10 maize plots were randomly selected for DNA fingerprinting of crop cuts. We compare key farmer and field characteristics of this DNA sample to the maize-growing plots in these regions for which DNA tests are not available. While the regional composition differs significantly in its weights, this comparison (Table A10) shows balance along most key characteristics between the DNA sample and the other maize plots. To infer the DNA type of seeds sown on plots not covered by the DNA fingerprinting, we use a machine learning approach to predict the DNA type for fields in the broader ESS sample.[13]

This approach allows us to train, validate, and optimally combine a group of candidate algorithms to generate an ensemble model for classifying whether a plot is sown with improved or traditional seed.[14] We then apply this model to all remaining plots in the major maize-growing regions.[15] The results are plot-specific predicted probabilities that the chosen variety is genetically improved.

3.2.2. Extrapolating nitrogen use to national level

Next, we combine self-reported beliefs for farmers outside the DNA subsample with the predicted probabilities for the DNA type of the seeds they are growing.[16] We sum these probabilities, weighted by the ESS4 sampling weights, for each belief type. To account for differences in plot size, we weight each probabilistic observation by the corresponding area and calculate population-weighted shares of total maize area for each group. We then apply these shares to the estimated total area in Ethiopia devoted to maize production in 2018/2019.[17] Additionally, we combine observed nitrogen use with population weights and predicted probabilities of each belief type to calculate the average nitrogen use per group.

[13] Specifically, we use a technique called *SuperLearner* (Van der Laan et al., 2007).

[14] Our candidate models include random forest, glmnet, xgboost, and bagged classification trees.

[15] Relaxing this restriction and predicting for all maize farmers in our sample regardless of their region produces similar under- and overuse estimates at the national level.

[16] If a farmer reported the seeds sown on a given plot as 'traditional', then these probabilities are constructed as $Pr(TP) = Pr(FP) = 0$, $Pr(FN) = P(DNA = improved)$, and $Pr(TN) = 1 - Pr(DNA = improved)$. If a farmer reported sowing 'improved' seeds, then these probabilities are: $Pr(TN) = Pr(FN) = 0$, $Pr(FP) = 1 - Pr(DNA = improved)$, and $Pr(TP) = Pr(DNA = improved)$.

[17] We take this estimate from the USDA estimate for the 2018/2019 season of 2,415,000 hectares, see https://ipad.fas.usda.gov/countrysummary/Default.aspx?id=ET&crop=Corn (Accessed 19 April 2023).

3.2.3. Estimating counterfactual nitrogen use under 'corrected' beliefs

In the previous step, we estimate the average observed nitrogen use at the national level for each of the four belief types. As an approximation exercise, we quantify the extent of over- and under-application of nitrogen for FP and FN farmers by constructing a counterfactual of 'corrected' beliefs. We first estimate a model of nitrogen application based on farmer characteristics in the major maize growing regions. We then employ this model to predict nitrogen application under an alternative of correct beliefs, as given by our estimated DNA probabilities. We then follow the approach laid out above to estimate the 'corrected' nitrogen use intensity per group.

Combining area and nitrogen use intensity estimates for FP and FN farmers, we arrive at estimates of group-wise nitrogen use under observed and corrected beliefs, which allows us to quantify the extent of nitrogen overuse and underuse. We refer to these as inefficiencies, but we use this term loosely, as we do not know what the optimal level of nitrogen usage is for the plots in our data.

4. Results

4.1. Seed beliefs and on-farm input allocation

We report our main results for effective nitrogen application (kg/ha) in Table 2. Table A7 reports comparable results for effective phosphorus use. In columns (1)–(3), we progressively expand the set of manually selected control variables included in the specification, which we estimate using OLS. In columns (4) and (5), we use PDS LASSO to select controls with "Belief" and "DNA" as treatment variables, respectively. Across these five estimations, we see consistently large positive effects of farmer beliefs on nitrogen use, including with PDS LASSO estimation (see Table 1 for average nitrogen use).[18]

The estimated coefficient on the "Belief × DNA" interaction is consistently large and negative, which somewhat surprisingly suggests that farmers with TP beliefs systematically apply significantly less nitrogen than those with FP beliefs.[19] Summing the first three estimates in column (4), on average TP farmers apply about 54 kg/ha more than TN farmers. FP farmers, by contrast, apply 49 kg/ha *more* than these TP farmers. This puzzling pattern could perhaps reflect the fact that FP farmers are less likely to have purchased their seed than TP farmers (Table 1). If farmers have a fixed budget for agricultural inputs – either literally or as a behavioral regularity – then a reduction in seed expenditures would leave these farmers with more of their agricultural input budget available for fertilizers. This explanation is consistent with supplemental results for total expenditure on purchased inputs reported in Table A8, which show insignificant coefficients on the "Belief × DNA" interaction – suggesting that while FP farmers spend more on and apply more fertilizer than their TP peers, their overall expenditure on inputs is comparable. An alternative explanation for this pattern is suggested by differences in reused seed: 17.5% of FP farmers report using saved or recycled improved seed whereas only 3.4% of TP do. Such farmers likely face more uncertainty about seed quality or genetic purity and may try to offset a perceived deterioration with more nitrogen.

Some caution is merited in interpreting these estimates as causal. However, the robustness of the estimates to the inclusion of a full set of controls – including a set chosen agnostically with PDS LASSO – is at least suggestive of a causal relationship between beliefs and fertilizer use. However, we cannot rule out the possibility that false seed beliefs are endogenous with respect to fertilizer use.

[18] Supplemental results indicate that these effects of beliefs on nitrogen use are driven by both extensive and intensive margin adjustments.

[19] Note, however, that this estimated coefficient is no longer significant when estimating the extensive and intensive margin adjustments separately.

Table 2
Effective nitrogen use, seed beliefs and DNA type.

Dependent variable:	(1)	(2)	(3)	(4)	(5)
Nitrogen (kg/ha)	OLS			PDS LASSO	
Belief	108.79***	135.04***	123.67***	**92.77******	122.02***
(improved = 1)	(29.18)	(39.61)	(36.95)	(35.18)	(35.79)
DNA	16.57	19.42*	19.71*	10.28	**16.33**
(improved = 1, 95% purity threshold)	(10.97)	(11.62)	(10.38)	(8.30)	(10.23)
Belief × DNA (TP = 1)	−66.77**	−62.10**	−51.38*	−48.99*	−51.30**
	(32.42)	(29.72)	(26.47)	(25.53)	(25.37)
Extension contact (yes = 1)		2.60	1.14	−33.32**	3.16
		(13.07)	(12.93)	(13.99)	(12.15)
Seeds purchased (yes = 1)		−35.82*	−29.07	−51.21	−34.05*
		(20.03)	(18.56)	(31.92)	(18.50)
Field size (ha)		−105.26***	−82.39***	−97.01***	−86.93***
		(32.93)	(29.41)	(30.95)	(29.99)
Manure use (yes = 1)		−4.22	−10.19	3.89	3.42
		(10.97)	(10.84)	(12.56)	(14.54)
OLS: Main controls (4)	no	yes	yes	yes	yes
OLS: Extended controls (12)	no	no	yes	yes	yes
PDS LASSO: No. of candidate controls				288	288
PDS LASSO: No. of selected controls				6	5
Observations	432	432	432	432	432
Adjusted R^2	0.16	0.20	0.24	0.28	0.24

Notes: The DNA indicator is 1 if the DNA test indicated improved genetic material at a purity threshold of 95%. Model 3 includes region indicators as well as the following 'extended controls': age, gender, 'has attended any school', access to credit services, mobile phone ownership, and household distance to nearest market, major road, and population center. Amounts of nitrogen are simple aggregates of the respective nitrogen contents of three fertilizers: Urea = 46%, DAP = 18%, NPS = 10%. Clustered standard errors robust to heteroskedasticity across enumeration areas in parentheses. The set of variables in model 4 and 5 selected by the LASSO and used in the OLS post-LASSO estimation and in the PDS structural estimation is augmented by an amelioration set ensuring that belief, DNA, and their interaction, as well as the extended controls enter the identifying model. Designated 'treatment' variables in the PDS LASSO printed in bold. See Belloni et al. (2014) for details.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

A natural question that emerges from these results pertains to the production implications of false belief-based input distortions. Do the patterns that we observe lead to a loss of output or profitability? Given the substantial heterogeneity in maize production conditions in Ethiopia (e.g., soils, agroecologies, etc.), it would be heroic to estimate a production function for this context, as there is no single, uniform yield-maximizing (much less, profit-maximizing) amount of fertilizer for farmers to apply. This has not historically prevented the Ethiopian government from providing and promoting uniform national fertilizer recommendations (Abate et al., 2015). As mentioned earlier, if we interpret these recommendations as profit-maximizing levels of nitrogen use and take them at face value, the vast majority of farmers in our sample under-use nitrogen. False seed beliefs may therefore distort nitrogen use in a way that increases rather than decreases profits.[20] Consequently, it is impossible to impose a general productivity interpretation on these results. What we can state with greater confidence is that these results suggest that false seed beliefs distort input allocations *relative to farmer intent*. Although we do not elicit fertilizer intent directly, the substantial effect of farmer beliefs on fertilizer use suggests that farmers who believed they sowed improved (traditional) seed intended to apply much more (less) fertilizer.

We can provide descriptive evidence of yield implications of these input distortions using the crop-cut based production measures and GPS-based plot size measurements for the plots in our subsample. Together, these gold-standard measures of area and output provide reliable yield data, which we present as cumulative distributions in Figure A3. Yield tends to be higher for true improved seeds – whether aligned with farmer beliefs or not – and for plots managed by farmers who believe they sowed improved seeds – whether aligned with the genetic truth or not. Recall from above that farmers with false positive beliefs apply heavier doses of nitrogen than those with true positive beliefs, which partly explains this observed yield pattern.

4.2. DNA prediction and projection of national nitrogen use

We employ a machine learning approach to predict DNA type for those maize plots in the major maize-growing regions that are not covered in the DNA fingerprinting and use these predictions to construct probabilistic estimates of our four belief types as described above. Panel A of Table 3 shows the results of this exercise. In this larger sample, 20% of farmers are predicted to be TP, 16% FP, 46% TN, and 17% FN. Calculations in Panel A also show that farmers with false beliefs occupy around 35% of the land used for maize cultivation in major maize-growing regions in Ethiopia.

For those sowing truly improved seeds, we see in Panel A that TP farmers use about 76 kg/ha of nitrogen on average compared to 20 kg/ha for FN farmers. The disparity for traditional seeds is much more stark: 99 kg/ha for FP farmers compared to 19 kg/ha for TN farmers. At the aggregate level, these gaps have the potential to produce quantitatively important misallocation of agricultural inputs. An optimal allocation of fertilizer should see farmers with the same seeds utilizing similar intensities of complementary agricultural inputs. Based on this assumption, we can quantify national-level over- and under-allocation of fertilizer by constructing a counterfactual scenario of 'corrected' beliefs for the FP and FN groups (see Appendix for more detail). We cannot definitively say that this represents a misallocation, since we do not know with any confidence what is the optimal level of fertilizer use. However, it is difficult to construct reasonable scenarios in which the discrepancy is efficient.

In Panel B, we report scaled estimates of nitrogen use at the national level by belief type. Using the counterfactual of 'corrected' beliefs described above, we also report what we predict total nitrogen use would have been with correct seed beliefs. We estimate that FP farmers as a group overuse nitrogen by around 20,301 t. FN farmers as a group underuse nitrogen by much less, 9,466 t.

[20] To elaborate on this point, Figure A2 suggests that while the median FP farmer applies the recommended amount of nitrogen, the median TP farmer applies about half the recommended amount.

Table 3
Predicting national-level rates of seed classification and nitrogen application.

Panel A: Population-weighted results by belief type	**True positive**	**False positive**	**True negative**	**False negative**
Shares of belief types	20%	16%	46%	17%
Shares of belief types, population-weighted	25%	16%	42%	16%
Shares of total maize area, population-weighted	39%	21%	26%	14%
Observed nitrogen use (kg/ha)	76.29	99.40	19.28	20.23
Predicted nitrogen use under correct beliefs (kg/ha)	–	59.32	–	49.05
Inefficient overuse (kg/ha)	–	40.08	–	–
Inefficient underuse (kg/ha)	–	–	–	28.82
Panel B: National-level estimates by belief type	**True positive**	**False positive**	**True negative**	**False negative**
National-level maize area (ha)	950,239	506,531	629,801	328,429
National-level nitrogen use under observed beliefs (t)	72,496	50,348	12,142	6,643
National-level nitrogen use under correct beliefs (t)	–	30,047	–	16,109
Inefficient overuse (t)	–	20,301	–	–
Inefficient underuse (t)	–	–	–	9,466
Panel C: Cross-validated model performance	**Accuracy**	**AUC**	**Precision**	**Recall**
Ensemble model (SuperLearner)	0.83	0.85	0.70	0.78

Notes: 224 different variables are available to the model-generating algorithm, and we employ a 6-fold cross validation to reduce overfitting. Percentages may not add up to 100 due to rounding. The total national-level maize area is calculated using the percentages from Panel A and an external estimate of 2,42 million hectare used for maize cultivation in Ethiopia (USDA, 2019). Further evaluation of the performance of the algorithms underlying the prediction can be found in the Appendix.

5. Conclusion

Our results show that significant differences in fertilizer application arise from farmers' beliefs – correct or incorrect – about the type of seeds they are growing. Because farmers apply complementary inputs based on their beliefs about seed varieties, misidentification of the genetics of their seeds has implications for input use. To the extent that different genetic types do, in fact, give rise to different optimal levels of input use, our results provide suggestive evidence for misallocation of agricultural inputs.

Our findings confirm earlier studies by Bulte et al. (2014) and Wineman et al. (2020) which highlight the importance of beliefs regarding the quality of agricultural technology on the allocation of complementary inputs – and subsequently, on agricultural productivity. More generally, the paper reinforces the concerns raised by Bold et al. (2017), showing the potentially negative effects of input quality uncertainty. The potential harm that we identify is not solely from the direct cost – that farmers may have paid a price premium for seeds that are genetically low-quality – but more significantly from the indirect costs associated with inefficient use of complementary inputs. Some farmers may be applying costly inputs on varieties with limited response. We also note the dynamic concerns mentioned above. Farmer seed misidentification will presumably affect profitability. Farmers who are disappointed with the economic returns of the seed and fertilizer that they have used may be dissuaded from trying future technology packages, including those recommended by agricultural extension services and agri-dealers.

The paper highlights the need for policy makers to closely monitor the seed quality present in the market. This is especially relevant in the context of Ethiopia's nation-wide introduction of direct seed marketing and the broader liberalization of its seed system. Our findings emphasize the need to ensure seed quality even if the government no longer controls the entire seed supply. Furthermore, interventions helping farmers to identify the seed they are using and to ascertain the purity and quality of seeds could also be beneficial.

Our findings emphasize the importance of a deeper debate about the diffusion of newly developed seed varieties and the driving forces of farmer misinformation in this context. This paper serves as a starting point for further research and demonstrates the need for more extensive data collection. Misinformation on planted seed types is widespread in rural Ethiopia. Combined with other emerging evidence, these findings raise the concern that such misinformation may be a prevalent problem elsewhere in sub-Saharan Africa.

Finally, our study adds to the growing body of evidence suggesting the need for caution in using farmer self-reports of "improved" and "traditional" varieties in micro analyses. DNA evidence is increasingly pointing to the problems of relying on self-reports. Estimates of varietal diffusion or returns to research (for example) may be badly in error if they are based on the self-reports. Nor can we conclude that the self-reported data would necessarily give rise to classical measurement error: there are systematic patterns of misidentification, suggesting the need for more complex adjustments. We note also that the costs and other barriers to DNA fingerprinting analysis have been greatly reduced in recent years, so that it is no longer implausible for studies to make some use of DNA-based checks on farmer seed identification (Kosmowski et al., 2019). Future work on varietal adoption should benefit from these new measurement techniques.

CRediT authorship contribution statement

Nils Bohr: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Tim Deisemann:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Douglas Gollin:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Frédéric Kosmowski:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Validation, Writing – original draft. **Travis J. Lybbert:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing.

Data availability

Complete replication data are available at: https://data.mendeley.com/datasets/k452sp5ff8/1.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2024.103349.

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