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Nonclassical Measurement Error and Farmers' Response to Information Reveal Behavioral Anomalies

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Abstract

This paper reports on a randomized experiment conducted among Malawian agricultural households to study nonclassical measurement error in self-reported plot area and farmers' responses to new information (the objective plot area measure) that was provided to correct nonclassical measurement error. Farmers' pre-treatment self-reported plot areas exhibit considerable nonclassical measurement error, most of which follows a regression-to-mean pattern with respect to plot area, and another 18 percent of which arises from asymmetric rounding to half-acre increments. Randomized provision of GPS-based measures of true plot area generates four important findings. First, farmers incompletely update mistaken self-reports; most nonclassical measurement error persists even after the provision of true plot area measures. Second, farmers update asymmetrically in response to information, with upward corrections being far more common than downward ones even though most plot sizes were initially overestimated. Third, the magnitude of updating varies by true plot area and the magnitude and direction of initial nonclassical measurement error. Fourth, the information treatment affects self-reported information about non-land inputs, such as fertilizer and labor, indicating that the effects of measurement error and updating spill over across variables. Nonclassical measurement error reflects behavioral anomalies and carries implications for both survey data collection methods and the design of information-based interventions.

JEL Codes: C83, C93, D83, Q12

Keywords: asymmetric learning, inattention, misperception, measurement error, land area, household surveys, Malawi, Sub-Saharan Africa.

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1. Introduction

Household survey data commonly exhibit considerable nonclassical measurement error (NCME) (Bound et al., 2001). This is true even for key assets and factors of production, like agricultural land, that are readily measurable and observable to the survey respondent, and that heavily affect farmers' incomes and livelihood. The measurement error literature largely treats NCME as an econometric challenge to overcome. This would be appropriate if NCME arises purely due to respondents misreporting their true, accurate beliefs about land holdings and other key variables. In that case, NCME carries no implications for behavior and respondents' decision-making processes; it is merely a statistical nuisance. Abay et al. (2021) show, however, that a large share of NCME in plot sizes reported by farmers in four African countries appears to reflect farmers' reporting mistaken beliefs, not misreporting of accurate beliefs.[1] Such findings suggest that NCME in household survey data not only matters for statistical inference but can also shed light on respondents' decision-making processes and behaviors in ways that may reveal actionable information, consistent with a longstanding behavioral economics literature that routinely finds that people often act upon mistaken beliefs or misperceptions (Tversky and Kahneman, 1973; Kahneman and Tversky, 1984; Angner and Loewenstein, 2012).

If at least some NCME reflects mistaken beliefs, then uncovering the nature and sources of NCME and their prospective implications for measurement and policy design becomes important for multiple reasons. First, mistaken beliefs might reveal smallholder farmer behavioral phenomena that drive these errors, such as inattention, self-esteem, or confirmation bias. As a burgeoning literature on "choice architecture" underscores, organizations worldwide increasingly design policies around behavioral anomalies (Thaler and Sunstein, 2009; Ariely, 2016), but the agricultural development community has been slow to do so.

Second, we know little about whether and how farmers incorporate objective information to correct mistaken beliefs, although this surely matters for information-based interventions, such as agricultural extension programming, cadastral surveys, and market information services. If there exists heterogeneity or asymmetries in learning – i.e., the updating of reported beliefs – or learning

[1] Berazneva et al. (2018), Burke et al. (2020), Wineman et al. (2020), Michelson et al. (2021) and Wossen et al. (2021) provide similar evidence of misperception in soil quality, plot size, crop variety, chemical fertilizer quality, and crop variety, respectively.

failures – i.e., limited or no updating of mistaken beliefs after receiving accurate information – that should inform the design and investment in interventions intended to mitigate misperceptions.

Third, while conventional wisdom suggests that information campaigns can ameliorate farmers' mistaken beliefs, the empirical validity of this assumption remains largely untested. Because some behavioral phenomena that may generate NCME (e.g., inattention, confirmation, and self-esteem bias) might also obstruct learning and updating of mistaken beliefs, implying that the effectiveness of information interventions may be limited and might vary across observable and unobservable characteristics of farmers. Different farmers may pay attention to different technological features – or 'objects' – as the multi-object and selective attention learning literatures emphasize (Gabaix et al., 2006; Hanna et al., 2014; Schwartzstein, 2014; Ghosh, 2016; Wolitzky, 2018; Gabaix, 2019; Nourani, 2019; Kohlhas and Walther, 2021; Maertens et al., 2021).

Fourth, mistaken beliefs about one object may spill over to affect beliefs and decisions about other objects. As such, the provision of information that is meant to correct NCME in self-reported plot areas may subsequently impact a farmer's reporting on other objects during the same household survey interview (as we demonstrate concerning fertilizer and labor inputs), and, given that some NCME reflects mistaken beliefs, prospectively the farmers' future decisions regarding these objects (which is beyond the scope of this paper). Both scenarios have implications for measurement, inference and policy. Understanding whether and how farmers respond to new information about the size and quality of one production input by adjusting their reporting of other agricultural inputs can help us understand survey data generating processes and farmers' decision-making process.[2] Misinformation spillovers generate correlated NCME, which considerably complicates econometric correction for measurement error, because incomplete correction of measurement error in the presence of correlated NCME can aggravate rather than reduce bias in key parameter estimates (Abay et al., 2019).

We embedded an information experiment within an agricultural household survey in Malawi, providing an uncommon opportunity to study the nature of NCME and learning in response to corrective information to subjects' erroneous self-reports regarding cultivated land areas. Part of the appeal of this design is that most economics studies on inattention, learning, or

[2] For example, if providing farmers with GPS measures of their plots' size affects self-reported input use, introducing GPS-based plot area measurement in follow-up longitudinal data collection (as part of national panel surveys or impact evaluation studies) may compromise the inter-temporal comparability of self-reported, non-land variables.

confirmation, self-esteem or self-serving bias study prediction tasks concerning choice *outcomes* – e.g., the returns to stock choices, entrepreneurial efforts, technology adoption, etc. or the welfare gains from consumption choices among goods or services (Foster and Rosenzweig, 1995; Handel, 2013; Hanna et al., 2014; Handel and Kolstad, 2015; Bhargava et al., 2017; Hastings et al., 2017; Kohlhas and Walther 2021). However, estimation of respondent learning about outcomes requires accurately specifying the outcome data generating process, typically represented as a production, cost, or profit function. The possibility always exists that a respondent's beliefs accurately reflect unobservable farmer attributes that cause their outcome distribution to deviate from the analyst's estimates. Our experimental design, by contrast, rules out the possibility of unobserved heterogeneity by studying directly measurable, observable, and valuable agricultural inputs. No unobservables should materially influence answers to questions such as: what is the size of this plot? Nor should it influence responses to questions about how much fertilizer or labor the farmer applied to the plot before or during planting. Errors in reporting observable production inputs almost surely reflect either misreporting or systematic behavioral errors that lead to mistaken beliefs. NCME in directly measurable inputs are less likely confounded by other, unobserved arguments to the respondent's mental model of the relevant data generating process.

Furthermore, failure to update completely in response to demonstrably accurate, corrective information about an objectively verifiable value, such as the size of a plot, signals asymmetric or incomplete learning – or even complete learning failures, i.e., no updating at all – carries important implications for information-based interventions, such as extension messaging, market information services, cadastral surveys, public health, and nutrition education. The literature on attention and learning typically focuses on learning about outcomes, technologies, or some other phenomena that are not directly observable. By studying response to corrective information about a directly observable variable, we offer a more direct test of incomplete learning of various sorts.

Consistent with many prior studies (e.g., Carletto et al., 2013; 2015; 2017; Kilic et al. 2017; Abay et al. 2019; Abay et al., 2021; Dillon et al., 2019), we find pervasive, mean-reverting NCME in farmers' self-reported plot areas and considerable asymmetric rounding to easy-to-remember half-acre increments. In view of the importance of land for social status and income generation in these agrarian communities, these findings suggest behavioral anomalies that have been documented in other contexts, in particular, inattention to important details and self-esteem bias.

Furthermore, the analysis reveals that farmers' updating of mistaken beliefs in response to information on their true plot size is remarkably incomplete and asymmetric, indicating a greater willingness to adjust beliefs up than down. Updating is stronger only among larger plots, but still asymmetric. These patterns are likewise consistent with inattention as well as confirmation and self-esteem biases. Moreover, the information treatment affects self-reported information on other, non-land inputs, such as fertilizer and labor, consistent with the hypothesis that farmers employ simplifying mental models – e.g., optimal prediction error (Hyslop and Imbens, 2001) – to track these variables. This implies that NCME in one production input likely propagates to other production inputs, generating correlated measurement error, which further complicates econometric correctives, because replacing an erroneous self-reported variable with an accurate measure of the same variable can aggravate rather than reduce bias in regression coefficient estimates if one cannot also correct for the correlated NCME in other variables (Abay et al., 2019). The scale and persistence of the NCME we observe almost surely has distributional and welfare implications, although estimating those effects falls beyond the scope of this paper.

2. Experimental Design and Data

The data come from a randomized experiment that was embedded into the Malawi National Crop Cutting Study (NCCS), which was implemented by the National Statistical Office (NSO) in 2019/20, in collaboration with the World Bank's Living Standards Measurement Study (LSMS) team. The NCCS was implemented in a national sample of 72 enumeration areas (EAs) selected at random from the sample of EAs that were scheduled to be visited by the Fifth Integrated Household Survey (IHS5) in the months of December 2020 and January - February 2021.[3] In each EA, 24 maize cultivating households were selected at random from the universe of maize cultivating households identified through a full household listing in each EA. Of the sampled households, 16 were selected at random for a separate crop cutting experiment and were subject to two visits (post-planting and crop cutting/post-harvest) – these comprise our treatment group – while the remaining 8 households were subject to a single, post-harvest visit – they serve as our control group.

[3] The IHS5, a nationally representative household survey, ran from April 2019 to April 2020, covering a sample of 11,472 households in 717 EAs. To access the anonymized survey data and documentation from the IHS5, please visit: https://microdata.worldbank.org/index.php/catalog/3818.

During the first, post-planting survey visit, each treatment group household completed a short parcel-plot-crop-level module on farm organization, which listed all parcels and plots within, in accordance with the IHS5 parcel and plot definitions.[4] Once the roster of parcels and plots was completed, one maize plot was selected at random. The manager of this plot was the target respondent for questions on the rest of the activities occurring on this plot. The target respondent then self-reported the plot area. Subsequent to the respondent self-reporting the selected plot size, the enumerator and respondent visited that plot together. The enumerator measured the plot area with a handheld Garmin eTrex 30 GPS unit,[5] then recorded and shared with the farmer both the GPS-based plot area and the measurement error in farmer-reported area vis-à-vis the GPS-based counterpart (both in levels and as a share of GPS-based plot area).[6] This was the information treatment, a demonstrably accurate measure of the plot area.[7] After finishing the plot visit, the enumerator and the farmer returned to the dwelling to administer the rest of the post-planting questionnaire, which asked the farmer to self-report labor, fertilizer and other inputs used on the plot before and during planting.

During a second, post-harvest visit to each treatment household,[8] the respondent was asked again to report the selected plot area, whose GPS-based measure had been shared with the respondent during the post-planting visit. If the self-reported plot area was different than the GPS-based plot area, the respondent was asked again his/her recollection of the GPS-based plot area. The respondent then re-reported all labor and non-labor inputs on the plot, in view of the possibility of non-labor input applications not having been finalized at the time of the post-planting interview.

Conversely, control group households received a single, post-harvest visit during which they completed a unified agricultural questionnaire, including the same self-reporting of plot size,

[4] A parcel is defined as a continuous piece of land that is not split by a river or a path wide enough to fit an oxcart or vehicle. A plot is continuous piece of land on which a unique crop or a mixture of crops is grown, under a uniform, consistent crop management system.

[5] After walking the perimeter of a given plot with the plot manager to identify the boundaries, the enumerators measured the area with the GPS unit. The NSO enumerators were experienced users of the handheld GPS technology, which was adopted by the NSO for land area measurement in 2010 in the context of the Third Integrated Household Survey and the Integrated Household Panel Survey (IHPS).

[6] Once the GPS-based plot area information was imputed into the Survey Solutions Computer-Assisted Personal Interviewing (CAPI) application, the measurement error was calculated and displayed automatically.

[7] We cannot gauge the extent to which the sampled farmers trusted the GPS-based plot area measures and therefore cannot test whether mistrust of objective evidence might help explain highly imperfect updating of self-reported plot area.

[8] The post-harvest visit was scheduled according to the households' harvest calendars, as the primary purpose of this visit was to harvest and weigh the crops on pre-designated crop cut sub-plots on the selected maize plot.

in one sitting prior to any plot visits. The only contact with these households was made during the time that the field teams returned to the EA for the post-harvest visit to the treatment households. At the conclusion of each interview, one maize plot was then selected at random, and the enumerator accompanied the farmer to the selected maize plot, whose area and plot outline was obtained using the handheld GPS device. This protocol mirrors the current interview flow in the household surveys that have been supported by the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) initiative, including the IHS5 for Malawi. Table A1 provides an overview of the fieldwork implementation timeline, and the distribution of interviews with treatment and control households over time.

3. NCME as a Window on Behavioral Anomalies

NCME in self-reported plot areas has been widely reported (e.g., Carletto et al., 2013; Carletto et al., 2015; Dillon et al., 2019; Abay et al., 2019; Gourlay et al., 2019, Abay et al. 2021). This analysis corroborates prior findings and allows us to make more nuanced observations and link these patterns to behavioral anomalies observed in the broader economics literature. These findings lay the foundation for section 4's exploration of the causal impacts of providing objectively verifiable information that might resolve NCME.

Table 1 reports the descriptive statistics for sampled households and plots. Most households are male-headed and literate with about three-quarters of them relying on farming as main source of livelihood. On average, the plots are half an acre while the average farm size is roughly 1.5 acres. Table 1 shows that the randomization worked. Most of the observable characteristics are balanced across the treatment and control groups, and we cannot reject the null hypothesis of jointly zero coefficients associated with the regressors in Table 1.[9] Most importantly, pre-treatment self-reported plot area appears to be statistically similar across the control and treatment group plots.

[9] The F-test statistic for the regression of the treatment indicator variable on the characteristics listed in Table 1 equals 1.14, with p-value=0.29.

Table 1: Balance between control and treatment groups

	Control group		Treatment group		Mean difference
	No. obs.	Mean	No. obs.	Mean	
Household head male (0/1)	558	0.738	977	0.713	0.025
Age of household head	558	44.26	977	44.663	-0.403
Household head literate (0/1)	558	0.76	977	0.738	0.022
Household head married (0/1)	564	0.739	982	0.732	0.007
Household head Christian (0/1)	558	0.81	977	0.801	0.009
Household head main occupation (farming) (0/1)	564	0.761	982	0.746	0.014
Household engaged in nonfarming (0/1)	564	0.124	982	0.119	0.005
Area: self-reported, post planting (acre)	564	0.642	982	0.610	0.032
Area: GPS (acre)	564	0.558	982	0.507	0.051*
Area: self-reported, post planting (log, acre)	564	-0.755	982	-0.796	0.041
Area: GPS (log, acre)	564	-1.042	982	-1.119	0.077
Farm size (acre)	564	1.474	982	1.398	0.076
Plot acquired through local admin or inherited	564	0.243	982	0.22	0.023
Plot acquired through rental or purchase	564	0.073	982	0.116	-0.043***
Plot under customary tenure system	564	0.832	982	0.833	-0.001
Pure stand cropping (0/1)	564	0.426	982	0.412	0.013
Soil type sandy or clay (0/1)	564	0.555	982	0.601	-0.046*
Soil color red or brown (0/1)	564	0.381	982	0.376	0.005
Slope of plot is flat (0/1)	564	0.644	982	0.678	-0.035
Soil quality good (0/1)	564	0.495	982	0.529	-0.034
Soil texture fine or very fine (0/1)	564	0.413	982	0.395	0.018
Soil texture coarse or very coarse (0/1)	564	0.138	982	0.153	-0.014

Notes: This table compares characteristics of control and treatment plots using information collected before the treatment. The last column provides mean differences across treatment and control group characteristics. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 reports the distribution of plot sizes and measurement error in the post-planting and post-harvest interviews. We present these discrepancies across quartiles of "true" plot size (based on GPS measurement) and report differences in terms of biases relative to the true size. That is, for each quartile and survey round we compute, (i) $Relative\ bias{:}PP\ = \frac{(\bar{X}_{SP}-\bar{X}_T)*100}{\bar{X}_T}$ for the post-planting, pre-treatment round and (ii) $Relative\ bias{:}PH\ = \frac{(\bar{X}_{SH}-\bar{X}_T)*100}{\bar{X}_T}$ for the post-harvest, post-treatment round.[10] Although the overall relative bias (at the sample mean) in self-reported plot size in the post-planting survey is just 18 percent, this disguises a strong, systematic pattern across the plot size distribution. Farmers overestimate the size of the smallest quintile of plots by

[10] $\bar{X}_{SP}$ and $\bar{X}_{SH}$ stand for average self-reported plot size in the post-planting and post-harvest interviews, respectively. $\bar{X}_T$ stands for average true plot size (measured using GPS device).

an average of 194 percent while they underestimate the largest quintile's plot sizes by an average of 11 percent. These findings are consistent with previous studies showing that self-reported area measurement suffers from regression-to-mean biases: overestimation for smaller plots and underestimation for larger plots (e.g., Carletto et al., 2013; Carletto et al., 2015; Dillon et al., 2019; Abay et al., 2019; Gourlay et al., 2019). There is not much difference between reporting biases in the post-planting and post-harvest periods, except for the last quintile. We investigate this fact further in the next sections. Considerable average overestimation is one striking feature of self-reported plot areas.

Table 2: Discrepancies between self-reported (SR) and GPS-based plot size measures

Plot size quartile	Observations	Mean SR: PP	Mean GPS	Mean SR:PH	Relative bias (%): PP	Relative bias (%): PH
0-25%	387	0.28	0.10***	0.28	193.73	198.52
25-50%	389	0.46	0.26***	0.47	74.03	76.85
50-75%	390	0.66	0.54***	0.66	23.93	23.23
75-100%	380	1.09	1.22***	1.14	-10.57	-6.30
Total	1,546	0.62	0.53	0.64	18.27	21.10

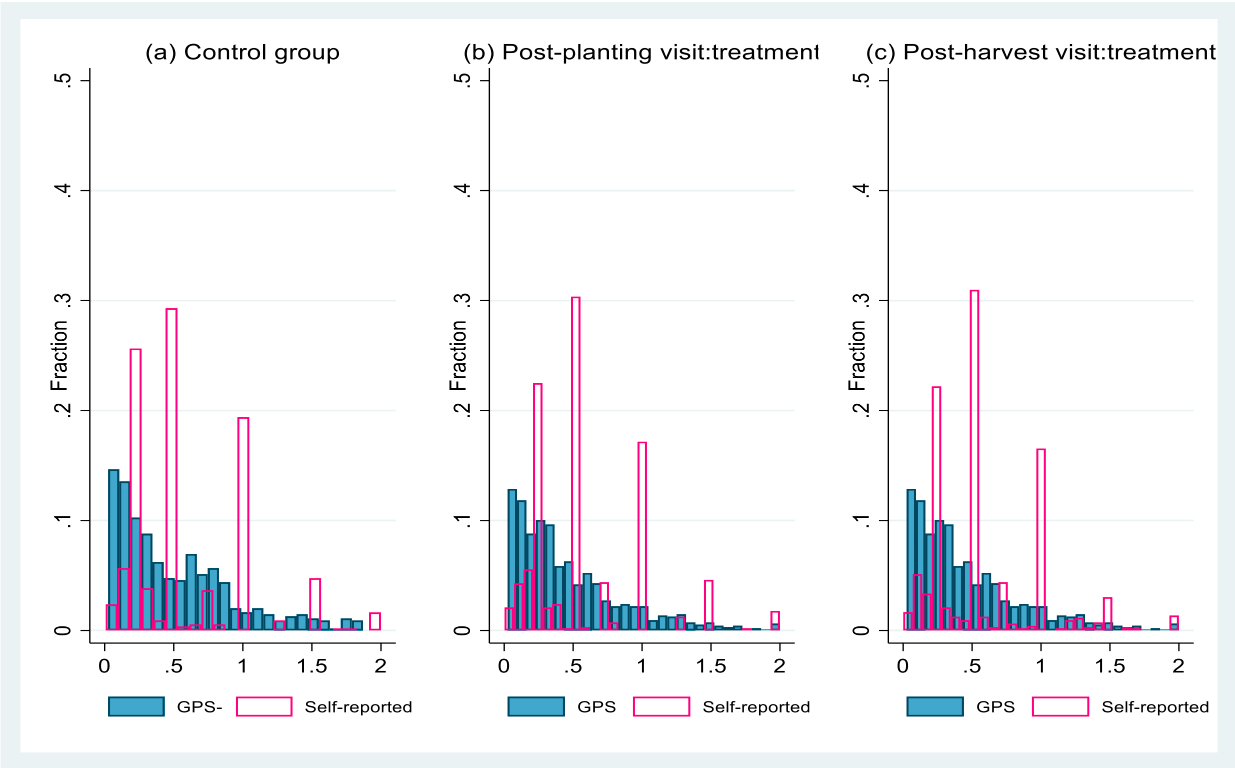
Notes: GPS stands for area measurement using handheld Global Positioning Systems, while SR stand for self-reported plot size in acres. PP stands for post planting visit while PH stands for post-harvest visit. These are quartile-specific mean and relative biases as a percent of (mean) GPS-measured plot size. *** Represents statistical test differences between GPS values and self-reported value in the post-planting survey.

Figure 1 shows that rounding is a major source of measurement error in self-reported plot area. Moreover, Figure 1 shows that heaping at focal points remained pervasive even after the true plot areas and the extent of measurement error were shared with treatment group farmers. About half of the self-reported plot sizes assume either of the four rounded values (0.5, 1.0, 1.5 or 2.0) in the post-planting and post-harvest interviews.[11] The slight differences in the distribution of plot sizes between the post-planting and post-harvest rounds appears to be only for those plots greater than 1 acre, where rounding at 1.5 and 2 acres slightly diminishes in the post-harvest survey. Appendix Table A2 reports Kolmogorov-Smirnov tests for differences between each pair of distributions in Figure 1. These non-parametric tests suggest that we cannot reject the null hypothesis of no significant differences between self-reported values across control and treatment groups, and between self-reported pre-treatment and post-treatment values within the treatment group. However, we can clearly detect statistically significant differences between self-reported

[11] The corresponding share associated with GPS-measured values is less than 3 percent.

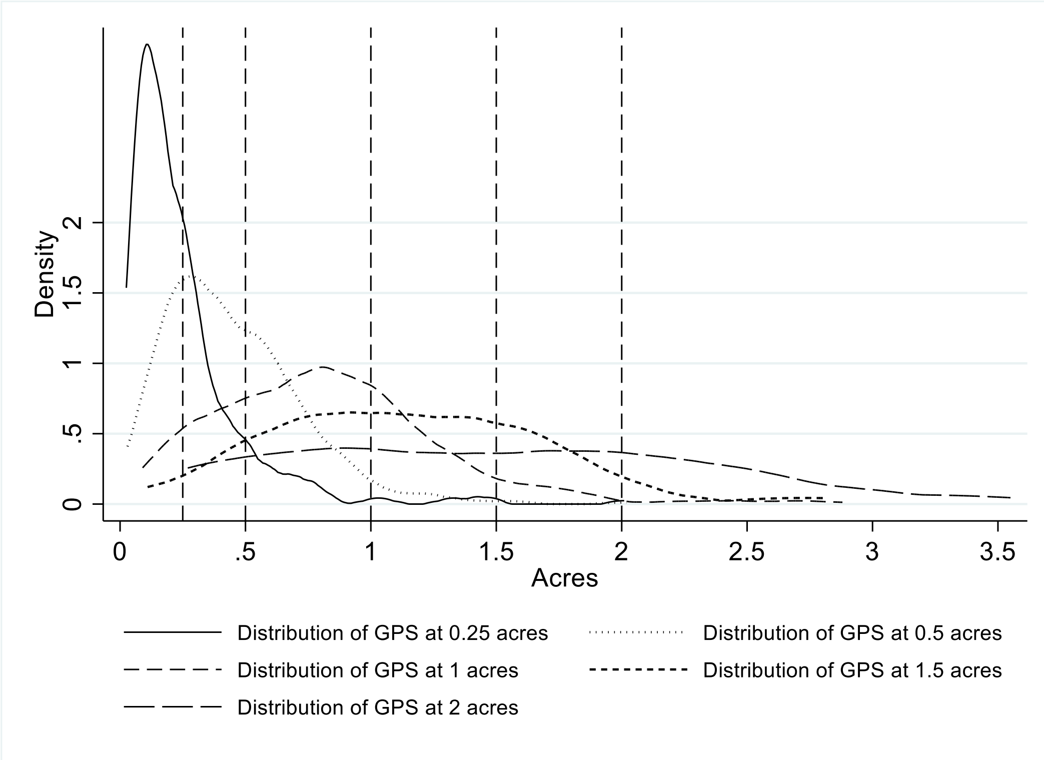
and GPS values, both for the control and treatment group plots. We explore some of these differences in the next section.

Figure 1: Distribution of self-reported and GPS plot size measures



Furthermore, the heaping around focal points is quite asymmetric. Figure 2 displays the distribution of GPS values across the most common self-reported focal values. The mode and median of GPS plot size measures consistently fall below the rounded, self-reported area. Farmers systematically asymmetric (upward) round at all plot sizes, although far more acutely for smaller plots, those less than 1 acre. Farmers are more likely to round upward than downward, but that likelihood decreases with true plot size. Overall, more than twice as many farmers overestimated their plot size than underestimated it (647 of 982 plots).

Figure 2: Distribution of GPS-based plot sizes at selected self-reported rounded intervals (post-planting)



We combine these features to explore parametrically the multivariate patterns in self-reported plot size measurement error. Table 3 reports the results from the regressions of (i) measurement error, computed as logarithmic differences between self-reported and objective measures, and (ii) overestimation and underestimation rates, each computed as the non-negative percentage difference between self-reported and GPS measure, as a function of observable plot-level and household-level characteristics. We also report the Shapley decomposition of the explained variation (measured by R^2) in measurement error over groups of regressors (Huettner and Sunder, 2012).

Table 3: Characterizing measurement error in plot size (post-planting round only)

	(1)	(2)	(3)	(4)
	Log (SR)-log(GPS)		%Overestimation	%Underestimation
	OLS estimates	Shapley	Tobit estimates	Tobit estimates
Plot size		**78.72%**		
Log (area: GPS)-centered	-0.680***		-210.759***	37.617***
	(0.017)		(6.953)	(1.859)
Log (area: GPS)-centered-square	-0.014		11.307***	8.928***
	(0.011)		(4.097)	(1.039)
Rounding of values		**18.28%**		
Rounding at 0.5 acre	0.419***		120.048***	-19.058***
	(0.034)		(11.903)	(2.781)
Rounding at 1 acre	0.905***		270.761***	-58.441***
	(0.042)		(15.149)	(4.025)
Rounding at 1.5 acre	1.186***		354.823***	-81.165***
	(0.070)		(24.455)	(6.902)
Rounding at 2 acres	1.430***		401.143***	-92.946***
	(0.096)		(32.847)	(9.508)
Household characteristics		**1.69%**		
Plot characteristics		**1.32%**		
Constant	0.006		-94.661*	-11.636
	(0.160)		(55.243)	(13.848)
Controls	Yes		Yes	Yes
Mean dependent variable	0.313		96.248	10.423
R^2	0.548	100%		
No observations	1535		1535	1535
No. censored observations	-		554	1035

Notes: The first column provides OLS estimates, and the second column reports Shapley decomposition associated with the R^2 in the first column. The third and fourth columns are Tobit estimates. Prior to expressing it natural logarithmic terms, GPS-based plot size was demeaned to center the data. Household characteristics include the female identifier, age, literacy, religion, marital status, and non-farm work status of the household head, as well as total farm size and number of plots managed. Plot characteristics include indicator variables for tenure status, rental or owned, pure stand cropping, soil type, and slope. Standard errors, clustered at enumeration area level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Appendix Table A4 reports full regression results.

Several important findings stand out from Table 3. First, measurement error is not random (i.e., classical) but rather is strongly correlated with a range of observables, as manifest in an R^2 of 0.55 in column 1. Second, measurement error is negatively and significantly correlated with true plot size, implying that larger (smaller) plots are more likely to be underestimated (overestimated), confirming prior findings of regression-to-mean patterns in area NCME. True plot size is the primary variable associated with NCME, accounting for 79 percent of the explained variation in measurement error. Third, the coefficient estimates on rounding indicator dummy variables for a self-reported plot size of 0.5, 1.0, 1.5 or 2.0 acres are statistically significant in all specifications, negatively (positively) correlated with under- (over-)estimation rates, confirming that farmers are more likely to round up than down (i.e., asymmetric focal point bunching). These rounding indicators together explain 18 percent of measurement error. Farmers with significantly larger and more plots are statistically significantly less likely to incorrectly report a rounded plot size (Appendix Table A3). Fourth, other observable plot and household level characteristics explain less than 3 percent of the variation in measurement error. Even though some such characteristics – e.g., farm size, the tenure status of the plot – are statistically significantly associated with plot size measurement error (see Appendix Table A4), these collectively make little difference to explaining measurement error. Fifth and finally, overestimation is proportionately far greater than underestimation; the mean overestimation is roughly double the true plot size while the mean underestimation is only 10 percent.

Systematic errors in self-reported plot areas are consistent with several behavioral phenomena identified in the broader behavioral economics literature. Various formal models exist to help isolate one or another of these phenomena. Because we study empirically several such phenomena at once, exploiting a field experiment to address prospective confounders, we remain agnostic as to which among many candidate structural models best explains the data, and eschew construction of a unified model of behavioral phenomena related to farmers' beliefs about salient features of their livelihoods. Rather, we tackle several key behavioral phenomena in turn, starting with inattention to salient information, then working through self-esteem and confirmation bias, in each case using the field experimental data to show the concepts' salience to smallholder farmers' reporting on their agricultural activities.

The first behavioral anomaly apparent in the NCME patterns is inattention to salient, observable information. Inattention to detail may be rational, in the sense that the costs of expending mental energy, space and time on remembering fine details may exceed the corresponding benefits of accurate recall of more granular information (Sims, 2010; Kohlhas and Walther 2021). Or maybe humans' memory is just imperfect, and people pay only selective attention to even key details they would benefit from remembering (Kahneman, 1973; Mullainathan, 2002; Schwartzstein, 2014; Gabaix, 2017). We cannot identify why our survey respondents appear inattentive to directly observable and highly salient information – the size of the plot they cultivate – i.e., whether NCME reflects frictions, mental gaps or both (Handel and Schwartzstein, 2018). However, only 31 out of 982 farmers (3.1 percent) had accurately self-reported their plot size (prior to the information treatment).

One would not expect farmers to exhibit uniform inattention to plot sizes for the simple reason that the costs of inattention likely vary predictably with observable farmer, farm, and plot characteristics. In particular, respondents who are more likely to incur greater financial or material losses from holding mistaken beliefs about farm size – e.g., those with larger plots – might be more likely to hold accurate beliefs that inform their production and marketing choices, and thus their incomes. Consistent with Kohlhas and Walther's (2021) model of asymmetric attention, farmers with larger plots are therefore less likely to round and exhibit measurement error of smaller relative magnitude. This may help explain the strong relationship between NCME and plot size.

Another natural result of inattention will be focal point heaping in reported plot sizes. If remembering detailed information is costly (i.e., rational inattention) or if people just do not bother to pay attention to key details then they likely do not respond "I don't know" but rather self-report, and perhaps believe, a simple proxy measure. [12] For example, a respondent who cultivates a 0.824-acre plot or a 1.107-acre plot may believe and report its size as one acre – leading to heaping around focal points that we observe in Figure 1.[13]

The mental cost of retaining precise information may not be the only reason for a farmer's mistaken beliefs about the amount of land she operates. People might favor false beliefs that boost their self-esteem.[14] A vast psychology literature finds that people routinely hold beliefs that boost their self-esteem (Pyszczynski et al., 2004).[15] In smallholder farming communities, land is not merely a critical production input; it is also a source of status and identity. If a farmer's utility rises with her (perhaps mistaken) belief in the size of her own plot or farm, then the (psycho-emotional) gains from mistakenly believing an inflated estimate of one's plot size may exceed the (material or

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[12] The survey also inquired about whether the plots had been measured in the past. Only 10 percent of treatment and control plots had ever been measured by any method, and of those, only 20 percent (i.e., 2 percent of our sample) had been measured with GPS. This pattern is balanced across the treatment and control groups, and while not shown here, the incidence of the plot having been measured by any method in the past is not a significant predictor of NCME. Those results are available upon request.

[13] Note that random misreporting would exhibit a regression-to-mean pattern, with no focal point bunching. There could be random misreporting around focal points, although in our data, the drop off from the focal point to surrounding values appears far too sharp for random misreporting to play a major role.

[14] Self-esteem bias is closely related to – arguably, it is a sub-set of – self-serving bias that has been widely studied and relates to the seemingly-unfounded confidence people often exhibit in their own ability and accomplishments (Camerer and Lovallo, 1999). We focus on self-esteem as the benefit that comes from overconfidence that may come at a price, as when people exaggerate their ability to pick winners in financial markets or to succeed in a job that requires technical skills. But where overconfidence in one's ability may actually improve performance (Compte and Postlewaite, 2004; Rabin and Vayanos, 2010; Rosenqvist and Skans, 2015) in ways that seem less likely for a farmer holding mistaken beliefs about her plot size.

[15] For example, students routinely overstate their achievements, resulting in the well-known "Lake Woebegone effect" (Maxwell and Lopus, 1994).

financial) costs of acting on erroneous information. Self-esteem bias could thus be rational, in the sense that it is a natural (if perhaps subconscious) choice in response to the non-material returns to retaining mistaken beliefs. The asymmetric errors and asymmetric focal point bunching evident in the data might reflect self-esteem bias, i.e., respondents are more likely to round up than to round down to the nearest simple fraction or integer because they feel better overstating rather than understating their land holdings. Misreporting or pure rational inattention should have symmetric effects on NCME in plot size.

The patterns of NCME evident in farmers' misreporting/misperception of a readily observable and measurable variable that matters a great deal to their livelihood seems to be a matter not only of concern for survey measurement and statistical inference, but also of interest for the behavioral insights they offer that might help inform policy design. Those insights are further corroborated by the experimental results from the information treatment we ran among these farmers.

4. Incomplete, Heterogeneous, and Asymmetric Learning

We observe plot size measurement error both before and after treatment group farmers observed the GPS measurement of their plot and were told the true area and the measurement error in the self-report they had provided earlier in that interview. Thus, whatever measurement error existed in the first survey round was easily and fully correctable before the subsequent round, which was fielded three to four months later. Studying treatment group farmers' response to that information treatment, on its own and in comparison to the control group, reinforces the prior section's suggestion of ubiquitous behavioral phenomena, especially inattention and self-esteem bias, compounded by confirmation bias.

Table 4 reports the distribution of measurement error for the control group and the treatment group pre-treatment (PP), as well as the treatment group post-harvest (PH) measure following the information treatment. Because we have already seen that NCME is strongly associated with plot size, we disaggregate results across plot size quartiles. In the absence of information treatment both control and treatment group farmers report statistically similar error in self-reported plot size for all plot size quintiles, consistent with the experimental balance we already established between the control and treatment groups (Table 1). Table 4 shows that pre-treatment the size of the error in self-reported plot size are statistically similar. As reflected by the significance indicators (* and #) in the last column of Table 4, the information treatment clearly affected the share of plots with under/overestimated plot sizes and differentially across the plot size distribution.

Table 4: Distribution of measurement error in plot size, before and after treatment

	Plot size quartile	Control group		Treatment group		
		Obs.	Mean	Obs.	Mean: PP	Mean: PH
Share of plots overestimated (binary):	Q1	141	0.865	246	0.907	0.886
Share of plots underestimated (binary):	Q1	141	0.128	246	0.077	0.061*
%Overestimation	Q1	141	229.455	246	259.170	266.113
%Underestimation	Q1	141	5.052	246	4.431	3.047
Share of plots overestimated (binary):	Q2	125	0.752	264	0.746	0.705
Share of plots underestimated (binary):	Q2	125	0.216	264	0.220	0.208
%Overestimation	Q2	125	92.405	264	78.352	80.046
%Underestimation	Q2	125	4.560	264	5.393	4.046
Share of plots overestimated (binary):	Q3	136	0.493	254	0.559	0.488
Share of plots underestimated (binary):	Q3	136	0.478	254	0.413	0.362*
%Overestimation	Q3	136	38.732	254	36.952	33.13
%Underestimation	Q3	136	14.127	254	11.394	7.49*[#]
Share of plots overestimated (binary):	Q4	162	0.383	218	0.390	0.376
Share of plots underestimated (binary):	Q4	162	0.599	218	0.560	0.39*[#]
%Overestimation	Q4	162	15.333	218	11.966	8.085*
%Underestimation	Q4	162	20.790	218	19.586	9.484*[#]

Notes: Overestimation and underestimation rates are computed as percentage difference between self-reported and GPS measures for values above zero and zero otherwise. That is, for each over(under)estimated plot we compute percentage difference between self-reported and objective measures. Standard errors in parentheses. Q1, Q2, Q3, Q4 stands for first, second, third and fourth quintiles of plot size. PP stands for post-planting round and PH stands for post-harvest round. * indicates that differences between control and treatment group are statistically significant while # implies that differences between post-planting and post-harvest values (for the treatment group) are statistically significant.

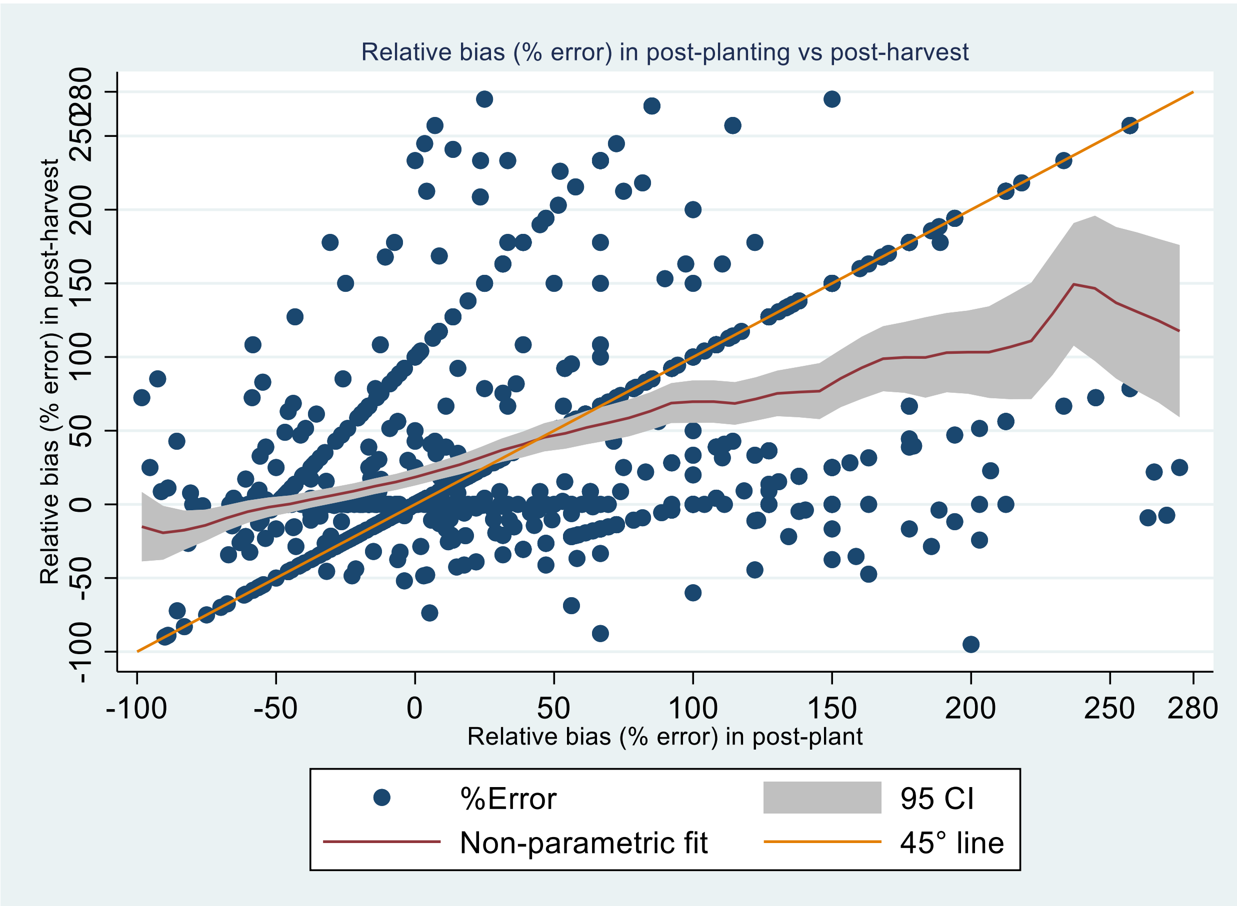
Three important patterns stand out from Table 4. First, adjustment in response to new information appears highly asymmetric. Farmers who underestimated their plot size initially are far more likely to update their answer, and by a larger amount, than those who had initially overestimated their plot size. Second, farmers with larger plots appear to respond more than those with smaller plots; differences between treatment and control group plot size measurement errors are only significant for the last two quartiles. Third, among the treatment group farmers, those with larger plots are more likely to update and correct their pre-treatment errors, as shown by the significant differences between pre-treatment and post-treatment values for the third and fourth quartiles. Consistent with other patterns of asymmetry already reported, farmers' revisions to their self-reported plot size are more pronounced among those farmers who underestimated their plots.

Incomplete updating is apparent in the scatter plot and nonparametric kernel regression displayed in Figure 3, which plots the percentage measurement error in the post-treatment (post-harvest) survey round on the vertical axis, against the pre-treatment measurement error. If the information treatment fully eliminated NCME, the scatter plot would be a horizontal line at the zero mark on the vertical axis. Only 13 percent of treated households report plot size accurately after receiving the GPS measure of the plot. Notably, those observations are heavily concentrated among respondents whose initial measurement error was modest, within roughly the [-50,50] interval. Meanwhile, only another 28 percent of households exhibit some correction of mistaken beliefs, as shown by the clustering of points around the zero value on the vertical axis and within the range bounded by zero and the post-planting measurement error. A plurality of farmers (37 percent) did not change their incorrect beliefs, which remained identically wrong over time, as depicted by the observations along the 45-degree line. It is striking that nearly three times as many farmers did not change their mistaken beliefs at all than fully updated to the correct plot size based on measurement they witnessed on an observable variable. The nonparametric regression indicates a strong, positive correlation between pre- and post-treatment measurement errors, but of shallower slope than the 45-degree line, signaling incomplete adjustment to corrective information, indicating partial learning failures.

Figure 3 reveals two other linear relationships in the pre- and post-treatment data. These reflect the propensity of respondents to report round values for plot area. To see this, define the self-reported plot size from survey round t (PP or PH), SR_t. true value, T (which does not vary over time, thus no subscript), and rounded values, R_i (with i indexing different positive integer multiples of 0.5, e.g., 0.5, 1.0, 1.5, 2.0). Then, for respondents who adjust from $SR_{PP}=R_1$ to $SR_{PH}=R_2$ with $R_1 \neq R_2$, $R_1 \neq T$ and $R_2 \neq T$, a linear relationship between measurement error in post-harvest and post-planting emerges with a slope $R_2/R_1 \neq 1$ as one varies T. For $R_1>R_2$ ($R_1<R_2$) the resulting linear relation has a shallower (steeper) slope than the 45-degree line. Since most of the rounded values take one of four values, these other lines demonstrate both respondents' propensity to round and the incomplete/incorrect updating of beliefs as they move from one incorrect, round self-report to another. The same share of treated households that fully corrected their pre-treatment erroneous self-report of plot size, 13 percent, instead switched from reporting one rounded,

mistaken value to another, clearly demonstrating the attraction of simple focal points and the incomplete nature of updating.

Figure 3: Persistence in measurement error



This point is reinforced in Table 5, which displays the transition matrix between the post-planting (pre-treatment) and post-harvest (post-treatment) self-reports to further probe information-induced changes in reporting patterns among treatment group households/plots only. Two key results are worth highlighting. First, adjustment in response to the corrective information on true plot size and the measurement error in the respondent's original self-report appears strikingly incomplete. The number of farmers reporting their plot size accurately after having been given the GPS measure of their plot increased fourfold, but only from 3 to 13 percent of treated farmers.[16] Of those who over- (under-)estimated initially, 76 (48) percent still over- (under-) estimated post-treatment.

Table 5: Information-induced changes in reporting behavior (treatment group plots only)

Post-planting reporting behavior	Post-harvest reporting behavior SR: Overestimate	SR: Underestimate	SR: Accurate	Total number of observations
SR: Overestimated	76.0	15.5	8.5	647
SR: Underestimate	36.5	48.4	15.1	304
SR: Accurate	22.6	0.00	77.4	31
Total number of observations	610	247	125	

Notes: Values are shares or percentage of plots over(under)-estimated across the post-planting and post-harvest rounds.

Second, the response of farmers to accurate information appears highly asymmetric. Those who overestimated their plot size pre-treatment remain highly likely to continue to overestimate it, while less than half of those who underestimated their plot size initially continue to underestimate post-treatment. Moreover, as shown in Table 6, the average magnitude of the overestimation hardly changes, with the difference statistically significant only at the ten percent level. Even though pre-treatment underestimates were only about one-fifth as large in percentage terms as overestimates, the average magnitude of change in underestimation was slightly larger, and the information-induced change had a highly significant effect in correcting underestimates. For instance, Table 6 shows that the average underestimation rate for the treatment group plots declined by 64 percent (from 32 percent to 12 percent) while the corresponding overestimation rate only declined by about 12 percent (from 149 percent to 131 percent). These results clearly reveal asymmetric responses both at the extensive (Table 5) and intensive margins (Table 6).

Table 6: Magnitude of information-induced changes in reporting behavior (treatment group plots only)

	Post-planting reporting behavior	**Post-harvest reporting behavior**		Difference between PP and PH
	ME magnitude in post-planting (%)	%Underestimation in post-harvest	%Overestimation in post-harvest	
Overestimated in post-planting	149.1(214.9)	3.5(11.9)	131.3(222.3)	17.8*
Underestimated in post-planting	31.8(22.5)	11.67(18.2)	34.1(128.0)	20.2***

Note: Values in bottom panel are mean percentage over/under-reporting in each round (standard deviations in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[16] In the pre-treatment survey, only 31 farmers accurately reported their plot size; this increases to 125 in the post-treatment survey.

Having already demonstrated that plot size is correlated with a farmer's propensity to over-/under-estimate plot size, we explore these relationships econometrically by estimating the following triple difference regression:

$$v_{ph} = \alpha_0 + \alpha_1 T + \alpha_2 X^* + \alpha_3 v_{pp} + \alpha_4 T X^* + \alpha_5 T v_{pp} + \alpha_6 v_{pp} X^* + \alpha_7 T v_{pp} X^* + \theta Z_p + \varepsilon \quad (1)$$

where v_{ph} stands for continuous (bidirectional) measurement error as well as percentage over- or under-estimation in the post-harvest, post-treatment survey, and T stands for an indicator variable for those households/plots exposed to the informational treatment, X^* stands for (log-transformed) GPS plot size measure, v_{pp} is pre-treatment measurement error in self-reported plot size,[17] Z_p is a vector of controls, additional observable characteristics of plots and households collected before the informational treatment, and ε is a mean zero error term. In the interest of exploring heterogenous and asymmetric responses we interact the treatment dummy with true plot size and pre-treatment measurement error. To facilitate interpretation, we center both the plot size and measurement error variables. The most important parameters in equation (1) are α_1, α_4, α_5, and α_7. α_1 quantifies the impact of the informational treatment at the average plot size and measurement error in our sample, when the centered X^* and v_{pp} variables take value zero. α_4 captures heterogeneous information impacts associated with plot size, holding constant pre-treatment measurement error. Similarly, α_5 captures heterogenous information impacts based on a farmer's prior misperception (measurement error), holding constant plot size. Finally, α_7 reflects the interactive effect of plot size and pre-treatment measurement error. Before we discuss estimation results, we note that farmers' response and adjustment to new information may not represent "learning" if farmers just change reporting behavior without updating their beliefs. This seems unlikely; thus, we interpret these changes as learning.

Table 7 reports results using continuous and bidirectional indicator of measurement error in self-reported plot size, both in the pre-treatment and post-treatment surveys. The dependent variable in Table 7 is given as log-transformed differences between self-reported and GPS values in the post-treatment round. Table 8 reports censored estimation results. The dependent variable in the first three columns in Table 8 is the post-treatment overestimation percentage, while the dependent variable in the last three columns is the underestimation percentage. Our preferred

[17] Because the post planting survey was only administered for treatment group plots, we use the (no treatment) post-harvest measurement error for the control group plots.

specifications are the third and sixth columns, i.e., those with full controls. We highlight a few interesting patterns that corroborate the descriptive results in the earlier sections.

Table 7: Bidirectional measurement error in plot size and the impact of information provision

	(1)	(2)	(3)
	Measurement error: Post-harvest [log(self-reported)-log(GPS)]		
Treatment	0.040	0.054**	0.063**
	(0.024)	(0.026)	(0.027)
Plot size	-0.000	-0.000***	-0.001
	(0.000)	(0.000)	(0.007)
Treatment x Plot size	-0.311***	-0.310***	-0.311***
	(0.042)	(0.041)	(0.044)
Measurement error-pre-treatment	1.000***	1.000***	0.995***
	(0.000)	(0.000)	(0.007)
Treatment x Measurement error-pre-treatment	-0.807***	-0.789***	-0.789***
	(0.075)	(0.072)	(0.070)
Measurement error-pre-treatment x Plot size		-0.000	-0.002
		(0.000)	(0.004)
Treatment x Measurement error-pre-treatment x plot size		0.034	0.035
		(0.043)	(0.043)
Constant term	0.310***	0.310***	0.323***
	(0.000)	(0.000)	(0.097)
Controls	No	No	Yes
Mean of dependent variable	0.334	0.334	0.337
R-squared	0.589	0.590	0.595
No. observations	1546	1546	1535

Notes: measurement error is computed as difference between log-transformed self-reported and GPS values, log(self-reported)-log (GPS). Standard errors, clustered at enumeration area level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The main coefficients of interest in Tables 7 and 8 are those that involve interactions between treatment and either pre-treatment measurement error or plot size. For example, the interaction between treatment and pre-treatment measurement error in Table 7 shows reasonably strong, albeit incomplete, response to information. While we can reject the null hypothesis of one-for-one correction of pre-treatment NCME, holding constant everything else, at mean plot size the information treatment does correct 79-81 percent of pre-treatment measurement error. This represents the level of correction at the mean plot size and pre-treatment measurement error and is expected to represent maximum adjustment. These results confirm that learning is incomplete – given that almost two-thirds of plots were overestimated pre-treatment – that overestimation remains much larger than underestimation after treatment, and that learning is asymmetric.

The third row, reporting the coefficient estimates on the interaction between treatment and true plot size, at mean pre-treatment measurement error, clearly shows the regression to the mean and asymmetric patterns evident in the descriptive statistics. The learning impact of information leads to a sharp, significant decrease in measurement error (mainly overestimation) as plot size increases. But the information treatment effect on underestimation does not vary significantly with plot size.

Table 8: Measurement error in plot size and the impact of information provision: Tobit Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	%Overestimation: Post harvest			%Underestimation: Post harvest		
Treatment	4.986	-9.288	-7.523	-0.811	-0.722	-0.659
	(10.919)	(14.116)	(14.307)	(2.008)	(2.023)	(2.098)
Plot size	-23.888***	-18.172***	-15.780**	5.991***	8.817***	8.874***
	(6.186)	(6.782)	(7.175)	(1.133)	(1.311)	(1.389)
Treatment x Plot size	-106.270***	-109.682***	-114.907***	1.975	-1.279	-1.254
	(14.292)	(14.620)	(15.156)	(2.139)	(2.146)	(2.235)
% SR overestimate pre-treatment	1.163***	1.461***	1.444***			
	(0.037)	(0.071)	(0.075)			
Treatment x % SR overestimate	-0.955***	-1.187***	-1.179***			
	(0.132)	(0.191)	(0.189)			
% SR overestimate x Plot size		0.213***	0.203***			
		(0.031)	(0.032)			
Treatment x % SR overestimate x Plot size		-0.175*	-0.169			
		(0.105)	(0.104)			
% SR underestimate pre-treatment				1.611***	1.706***	1.715***
				(0.069)	(0.075)	(0.080)
Treatment x % SR underestimate				-1.175***	-1.308***	-1.315***
				(0.115)	(0.126)	(0.127)
% SR underestimate x Plot size					-0.222***	-0.231***
					(0.052)	(0.051)
Treatment x % SR underestimate x Plot size					0.319***	0.320***
					(0.085)	(0.083)
Constant	27.234***	44.877***	83.410***	-14.051***	-14.298***	-10.221
	(8.000)	(7.365)	(31.852)	(2.511)	(2.451)	(6.255)
Control	No	No	Yes	No	No	Yes
Mean of dependent variable	96.008	96.008	96.343	7.994	7.994	7.889
Log-likelihood value	-6605.072	-6595.574	-6541.613	-2479.611	-2471.024	-2441.668
No. observations	1546	1546	1535	1546	1546	1535
No. censored observations	591	591	591	1,092	1,092	1,092

Notes: These results represent Tobit estimates characterizing over and underestimation rates. Overestimation and underestimation rates are computed as percentage difference between self-reported and GPS measures for values above zero and zero otherwise. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The triple interaction term in Table 8 is statistically insignificant and of low magnitude for over-estimation. This indicates that learning is associated both with plot size – those with larger plots update more – and initial errors – the biggest initial errors likewise draw the largest corrections in beliefs – but the two associations are largely independent of one another. By contrast, information leads to some "over-correction" of underestimation with increasing plot size and at mean NCME.[18] This is consistent with heterogenous response (across plot size) to the informational treatment; farmers with larger plots react more and hence are more likely to over-correct in response to the treatment.

This pattern of asymmetric, incomplete updating of mistaken beliefs in response to demonstrably accurate, corrective information about an objectively measurable, important input is consistent with pure inattention models. But it could reflect inattention combined with either self-esteem bias – people are less reluctant to reduce than increase their perceived holdings – or confirmation bias, the tendency to update beliefs more in response to new information that supports one's prior (self-serving) beliefs, even if mistaken (Rabin and Schrag, 1999). While confirmation bias would discourage farmers from updating mistaken beliefs, self-esteem bias will ameliorate that tendency in just one direction. Combining all three phenomena – which are to some degree observationally equivalent in this context – we would predict that farmers presented with accurate corrective information on true plot size update their mistaken beliefs about their landholdings more frequently – and/or by a larger magnitude – when told their plot is larger than they had previously believed. They want to believe information that boosts their self-esteem more than information that might diminish it. It is hard to otherwise explain asymmetric stickiness in mistaken beliefs.

Likewise, the cost of inattention or the financial or material losses from holding mistaken beliefs likely vary across plot and farm size, perhaps explaining heterogenous adjustments in response to demonstrably accurate information as a form of rational inattention. Further, the cost of not responding (inattention) to corrective information may increase with the magnitude of error in one's prior, mistaken beliefs, or with the overall plot size. Those with larger plots or who held more erroneous prior beliefs would respond more to a trustworthy information signal and update their beliefs accordingly. The heterogenous responses we document are consistent with this conjecture, although we cannot cleanly test those hypotheses. Prior studies have shown

[18] The notion of over-reaction to new informational treatment is well-studied in macro-level economic variables and may be explained by some of the behavioral phenomena generating heterogenous responses to information. For example, Kohlhas and Walther (2021) show asymmetric attention to various dimensions/attributes of information may generate both over and under-reactions to new information.

asymmetric and incomplete updating of existing beliefs among smallholders in Africa (Lybbert et al., 2007) and households and firms (Kohlhas and Walther, 2021).

5. Spillover Effects on Farmer Self-Reporting on Non-Land Inputs

If farmers exhibit misperceptions of plot sizes that vary little over time and adjust only incompletely to corrective information, one might then likewise expect inattention to inputs that vary more over time, and are often worth less, such as fertilizer applications or agricultural labor time allocation. One economical way for people to conserve on attention to details would be to hold a single belief about a central value – e.g., plot size – and then estimate other variables' values based on a simple, stable prediction rule that takes the single belief as its argument – e.g., a seeding or fertilizer application density or a rate of labor use per unit land cultivated – consistent with the notion of optimal prediction error (Hyslop and Imbens, 2001).[19] For example, fertilizer applications are usually recommended per unit of land, farmers may easily use that information to predict their applications.[20] Our experimental design allows us to test whether the randomized provision of plot size information indeed propagates to farmers' self-reports of other input application rates – that could not have actually changed – thereby signaling information spillovers because the new information on one production input (land) affects respondents' reporting of other production inputs (e.g., fertilizer, labor). [21] This would also signal that NCME in such variables are likewise correlated.

We focus on farmers' reported use of labor and fertilizer prior to and during planting, information that was collected from treatment group farmers immediately after they received the corrective information of the GPS plot size measure. Behavioral adjustments could cause real adjustment in later season input application rates in response to corrective plot size information, hence our focus on input application that would have all occurred prior to the pre-treatment survey data collection. We focus on labor and fertilizer because they are the most widely used non-land

[19] Other types of measurement error models may also generate similar spillover effects (e.g., Schennacha, 2020).

[20] Similarly, measuring labor application in a specific plot can be difficult because of the (staggered) nature of farming activities. In this case, farmers may use the size of the plot to get a sense of the labor needed for some of these farm activities (e.g., land preparation, weeding and harvest).

[21] An alternative mechanism could be that information that reveals to a respondent that he mis-estimated plot size may cause him to adjust all self-reports, regardless of whether they relate to plot size or not. Because the plot size information experiment and subsequent questions about input application on the plot were the last module of the post-planting questionnaire, we unfortunately have no variables clearly unrelated to plot size on which to test this alternative hypothesis about the mechanism behind the information spillover effect.

inputs and because they are typically applied roughly in proportion to the amount of land cultivated. Farmers therefore have strong motives to know and use the true plot size in deciding how much of those inputs to apply.

We define log-transformed input use (Y) and objectively measured plot size (X^*) and estimate the following input demand function for each input:

$$Y - X^* = \beta_0 + \beta_1 T + \beta_2 X^* + \beta_3 v_{pp} + \beta_4 + \beta_5 + \beta_{56} Z_p + \epsilon \qquad (2)$$

where the dependent variable is the input intensity (i.e., input use per unit of land), with Y standing for log-transformed input use in the post-planting round. All other terms are as defined in equation (1). The most important parameters in equation (2) are β_1, β_4, and β_5. The parameter β_1 estimates the impact of the information treatment on farmers' input self-reporting at the average plot size and measurement error in our sample. Rejecting the null hypothesis that $\beta_1 = 0$ indicates information spillovers across self-reported variables. β_4 (β_5) captures differential spillover effects associated with plot size (pre-treatment measurement error in plot size). To allow for asymmetric and heterogenous responses, we employ continuous over/underestimation rates in the pre-treatment survey.

One important assumption in the estimation of equation (2) is that recall length does not affect reporting differently for treatment and control groups. As discussed previously and shown in Appendix Table A1, the control group households were subject to a single post-harvest visit, while the treatment group households were visited once during the post-planting period (at the time of the information treatment) and once during the post-harvest period (together with the control group households in the same EAs). This assumption seems reasonable, for at least two reasons. First, Wollburg et al. (2021), studying earlier rounds of the same Malawi household survey, show that self-reported unconditional fertilizer quantity per plot is insignificantly associated with recall length and that self-reported farm labor activity (e.g., land preparation and planting, weeding and fertilizing) per plot is inconsistently and only modestly associated with recall length. Second, when we regress post-harvest self-reported fertilizer inputs against post-planting self-reports of the same variable among the treated households, the resulting coefficient estimate (0.955) is not statistically significantly different from one and the simple bivariate relationships explains almost half of variation, indicating a close correspondence between reports of the same early season input use regardless of whether collected post-planting or post-harvest.

Tables 9 and 10 report the conditional factor demand functions for early season (i.e., pre-planting and planting period) fertilizer and labor, respectively, the former estimated at both the intensive and extensive margins since there are many zero-valued observations.[22] The results highlight four intuitive findings. First, the provision of true plot size information has zero effect on fertilizer use reporting at the extensive margin. Farmers know whether they used fertilizer or not and that self-report is unaffected by corrective information about plot size. Fertilizer use, as a binary variable, is positively associated with plot size only and unrelated to either pre-treatment plot size measurement error or corrective information.

Second, the plot size information treatment significantly affects farmers' self-reported fertilizer use at the intensive margin, by roughly 7 percent of mean fertilizer use at mean plot size and pre-treatment measurement error (-0.298/4.244). Since the average farmer overestimates his plot size, corrective information on average told him that he was overestimating his area. This finding indicates that informational treatment induces farmers to reduce their estimates of fertilizer use intensity, too. Since farmers were asked to report their fertilizer use minutes after they witnessed the GPS measurement of their plot and were told the true plot size and the measurement error in their self-report of plot area, there was no opportunity for any actual adjustment in fertilizer use. These are pure spillover effects on beliefs, or at least on self-reports, caused by corrective information on a related but different variable. This raises concerns about the quality of self-reported data on fertilizer and labor inputs in agricultural household surveys, an issue that has received limited attention in the evolving discussion of improved household survey methods. NCME in non-land inputs may affect inferences about the determinants of and marginal returns to inputs (e.g., Abay, 2020).

Third, the treatment effects are systematically heterogeneous, varying especially with plot size. Farmers owning larger plots adjusted their self-reported fertilizer use intensity downwards by a larger amount. Without treatment, we find only a mild inverse relationship between input use per acre and plot size – the so-called Boserup hypothesis (e.g., Boserup, 1965; Ruthenberg, 1980; Binswanger-Mkhize and Savastano, 2017; Abay et al., 2021) – statistically significant at only the

[22] We emphasize that the objective of this estimation is to explore the extensive and intensive margins separately. We have no instrument to identify the selection component, thus identification in the second stage comes solely through the nonlinearity of the first-stage probit estimator. Estimation results involving triple interaction terms are given in Appendix Tables A5 and A6.

10 percent level. But that effect becomes strongly significant among farmers who receive the information treatment.

Table 9: Information spillovers on self-reporting of early season fertilizer application

	Fertilizer applied (yes=1, no=0) (1)		ln (fertilizer/acre) (2)	
Treatment (yes = 1, no = 0)	0.198	0.100	-0.325**	-0.298**
	(0.464)	(0.452)	(0.146)	(0.143)
ln(plot size)	0.220***	0.231***	-0.233	-0.239*
	(0.072)	(0.069)	(0.213)	(0.138)
Treatment • ln(plot size)	-0.046	-0.060	-0.209**	-0.237***
	(0.094)	(0.090)	(0.082)	(0.088)
SR overestimated (yes = 1, no = 0)	0.139	0.148		
	(0.371)	(0.360)		
Treatment • SR overestimated	-0.381	-0.325		
	(0.453)	(0.443)		
SR underestimate (yes = 1, no = 0)	0.145	0.201		
	(0.385)	(0.376)		
Treatment •SR underestimated	-0.297	-0.303		
	(0.475)	(0.471)		
% SR overestimate			0.001***	0.001***
			(0.000)	(0.000)
Treatment • % SR overestimate			-0.001***	-0.001***
			(0.000)	(0.000)
% SR underestimate			-0.007***	-0.007***
			(0.002)	(0.002)
Treatment • % SR underestimate			0.002	0.003
			(0.004)	(0.004)
$\widehat{IMR}$			-0.274	-0.406
			(1.825)	(1.164)
Controls	No	Yes	No	Yes
Mean of dependent variable	0.674	0.674	4.242	4.244
R-squared			0.177	0.193
No. observations	1546	1535	1042	1034

Notes: All plot sizes are natural logarithms of GPS measures, demeaned to center the data. SR indicates self-reported data. % over-/under-estimate is computed as percentage difference between self-reported and GPS measures for values above zero and zero otherwise. IMR is the inverse Mills ratio from the first-stage probit of fertilizer application. Fertilizer application includes only fertilizer applications before or during planting. Standard errors, clustered at enumeration area level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Fourth, we again find evidence of (mildly) asymmetric response. Farmers adjust fertilizer use intensity self-reports more sharply the greater their pre-treatment overestimation of their plot sizes. We do not observe similarly significant adjustments among those farmers who had initially underestimated their plots.

Table 10 reports estimation results on self-reported early season labor application intensity (i.e., labor per hectare, in person days). The first two columns include household and hired labor, while the last two columns show estimates for household labor only. There is some similarity with the observed spillover effects of plot size information on fertilizer use intensity. We see statistically significant asymmetric response, downward adjustment in self-reports of early season labor use intensity among those farmers who had overestimated plot size pre-treatment, but not among those who overestimated.

The labor use patterns differ in important ways from those with respect to fertilizer, however. In particular, the information treatment had no significant impact on labor intensity self-reports at mean plot size and pre-treatment measurement error. Furthermore, a significant inverse relationship exists between labor intensity and plot size in the absence of information treatment and is not statistically significantly affected by the corrective information. Measuring labor applications in smallholder farming is challenging (Arthi et al., 2018); the evidence here suggests one added complication: the possibility of correlated measurement error with plot size (Abay et al. 2019).

The findings in Tables 9 and 10 suggest that farmers employ simplifying mental models – e.g., optimal prediction error (Hyslop and Imbens, 2001) – to track some variables. This has two important implications in terms of understanding survey data generating processes. First, the presence of NCME in one production input likely propagates to other production inputs. Given the empirical regularity of NCME in smallholder plot sizes and farm sizes (Carletto et al., 2013; Carletto et al., 2015; Desiere and Jolliffe, 2018; Abay et al., 2019; Dillon et al., 2019; Gourlay et al., 2019), this implies likely NCME in fertilizer, labor, seed, and other inputs that have been less well studied. Second, simplifying mental models naturally generate correlated measurement error, which further complicates econometric correctives, as replacing an erroneous self-reported variable with an accurate measure of the same variable can aggravate rather than reduce bias in regression coefficient estimates due to correlated NCME (e.g., Abay et al., 2019).

We run several robustness checks to probe the robustness of our main results. Among these, we limit our sample to those cases where we have the same respondent in both the post-planting and post-harvest surveys. We re-estimate for these restricted sample involving the same respondent. Appendix Tables A6-A9 show adjustment in plot size self-reports in the post-harvest survey round. These estimates confirm those in Tables 7-10, confirming the already-discussed patterns of heterogenous and asymmetric responses and spillover effects of corrective informational treatment (on plot size) on other, non-land inputs.

Table 10: Impact of information provision on reporting of early season labor application

	(1) Log (total labor, person days/acre)	(2) Log (total labor, person days/acre)	(3) Log (household labor, person days /acre)	(4) Log (household labor, person days /acre)
Treatment (yes = 1, no = 0)	0.022	0.003	-0.006	-0.012
	(0.052)	(0.052)	(0.058)	(0.057)
ln (plot size)	-0.323***	-0.317***	-0.345***	-0.347***
	(0.041)	(0.042)	(0.043)	(0.044)
Treatment • ln (plot size)	-0.095	-0.075	-0.104*	-0.079
	(0.059)	(0.060)	(0.061)	(0.061)
% SR overestimate	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Treatment • % SR overestimate	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
% SR underestimate	-0.005**	-0.005**	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Treatment • % SR underestimate	-0.002	-0.001	-0.001	-0.000
	(0.002)	(0.003)	(0.003)	(0.003)
Constant	4.205***	4.250***	4.106***	4.171***
	(0.043)	(0.147)	(0.047)	(0.145)
Controls	No	Yes	No	Yes
Mean of dependent variable	4.216	4.223	4.099	4.106
R-squared	0.269	0.297	0.250	0.278
No. observations	1540	1529	1538	1527

Notes: All plot sizes are natural logarithms of GPS measures, demeaned to center the data. SR indicates self-reported data. % over-/under-estimate is computed as percentage difference between self-reported and GPS measures for values above zero and zero otherwise. That is, for each over(under)estimated plot we compute percentage difference between self-reported and objective measures. Labor application includes labor allocations before or during planting (for land preparation, planting, and ridging). Standard errors, clustered at enumeration area level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. Conclusions

Leveraging a unique experiment embedded into a national agricultural survey in Malawi, this paper investigates the extent, drivers, and persistence of NCME in farmer-reported plot areas. We also examine how farmers learn and adjust to demonstrably accurate information about plot size, both in terms of correcting pre-existing measurement error in plot size as well as their reporting behavior (responses) on non-land agricultural inputs.

Prior to the information treatment, farmers' self-reported plot areas exhibit considerable NCME. Measurement error is negatively correlated with true plot size, which accounts for close to 80 percent of the explained variation in measurement error. Asymmetric rounding of self-reported plot areas at half-acre increments accounts for the second major source of measurement error, accounting for 18 percent of the explained variation. Further, focal point bunching around simple rounded values is highly asymmetric, with farmers more likely to round up than down, especially at smaller plot sizes.

Perhaps most strikingly, NCME persists within the treatment group in follow-up (post-harvest) interviews conducted three to four months after the information treatment during the post-planting period. Even though plot size is directly observable and farmer subjects witnessed GPS measurement and were directly provided the true plot area and were informed of the error in their prior self-report of that variable, updating was far from complete. Further, farmers' updates of their self-reports are asymmetric. Upward corrections are more common than downward ones. The magnitude of updating in self-reported plot areas also varies by true plot area as well as with the magnitude and direction of the pre-treatment error in self-reported information. Finally, receiving information on true plot area and the extent of measurement error in self-reports affects subsequent farmer reporting on plot-level fertilizer and labor inputs, indicating that the effects of measurement error and updating spill over across variables and that survey data on non-land agricultural inputs may likewise contain significant NCME that correlates with the measurement error in plot area, with direct implications on the estimates of marginal returns to these inputs and a range of behavioral and policy parameters of interest.

We cannot identify the causal mechanisms behind these observations, which clearly merit further investigation. The absence of quick correction of demonstrably mistaken beliefs seems surprising given that rural households in Malawi depend heavily on land to generate income. Farmers have strong motives to know the true size of their plots. The fact that NCME is so widespread in such a readily observable, important input and that farmers learn and correct their errors incompletely and asymmetrically strongly signals likely behavioral anomalies that matter for (a) the design and implementation of information-based interventions that aim to ameliorate mistaken beliefs/persistent learning failures and improve agricultural and welfare outcomes, and (b) survey data collection and statistical inference. Regarding the latter, in view of the effects of the information treatment on subsequent reporting on agricultural inputs and the insights from existing research on correlated NCME in survey-based measures of agricultural production and inputs, methodological research should accelerate to develop improved survey data methods for agricultural inputs, mirroring the push for the adoption of objective survey methods for the measurement of land areas (via GPS) and crop productivity (via crop cutting) in household and farm surveys. Finally, these results raise important questions about whether and how corrective information - about plot size or other inputs – to correct farmers' mistaken beliefs improves input allocation and related decisions, thereby addressing apparent allocative inefficiencies that are strongly associated with productivity and welfare indicators. Longitudinal survey data collection on treatment and control farmers in subsequent agricultural seasons may help shed light on this hypothesis.

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Online Appendix

Table A1: Fieldwork Implementation Timeline

Post-Planting Fieldwork for Treatment Households		
Start Date	21 December 2019	
End Date	4 March 2020	
Interviews by Month	No. observations	Share
Dec-19	83	7.2%
Jan-20	560	48.4%
Feb-20	499	43.1%
Mar-20	16	1.4%
TOTAL	1,158	100%
Harvesting Fieldwork for Treatment Households		
Start Date	10 March 2020	
COVID-19 Break	17 April - 17 May 2020	
End Date	15 July 2020	
Interviews by Month	No. observations	Share
Mar-20	405	36.7%
Apr-20	319	28.9%
May-20	234	21.2%
Jun-20	143	12.9%
Jul-20	4	0.4%
TOTAL	1,105	100%
Fieldwork for Control Households		
Start Date	18 March 2020	
COVID-19 Break	17 April - 19 May 2020	
End Date	5 July 2020	
Interviews by Month	No. observations	Share
Mar-20	8	1.4%
Apr-20	42	7.3%
May-20	89	15.4%
Jun-20	390	67.5%
Jul-20	49	8.5%
TOTAL	578	100%

Table A2: Kolmogorov-Smirnov tests for differences between each pair of distributions

Comparison	K-S value	P-value (K-S<K-S*)
Control-treatment: pre-treatment	0.0252	0.977
Control-treatment: post-treatment	0.0258	0.970
Post-planting-Post harvest (for treatment group)	0.0326	0.674
Self-reported vs GPS: control group	0.2571	0.000
Self-reported vs GPS: treatment group: Pre-treatment	0.2383	0.000
Self-reported vs GPS: treatment group: Post-treatment	0.2627	0.000

Notes: these values represent Kolmogorov-Smirnov test statistics for differences between each pair of distributions.

Table A3: Explaining rounding patterns (post-planting)

	(1) Rounding (dummy)	(2) Rounding (dummy)	(3) Rounding incorrectly (dummy)	(4) Rounding incorrectly (dummy)
Log (area: GPS)-centered	0.220***	0.219***	0.204***	0.204***
	(0.012)	(0.012)	(0.012)	(0.011)
Log (area: GPS)-centered-square	-0.030***	-0.028***	-0.031***	-0.029***
	(0.010)	(0.010)	(0.010)	(0.010)
Gender of household head		-0.043		-0.020
		(0.039)		(0.042)
Log (household head)		0.038		0.054*
		(0.033)		(0.032)
Household head literate (0/1)		0.015		0.004
		(0.025)		(0.026)
Household head married (0/1)		0.011		-0.012
		(0.041)		(0.042)
Household head Christian (0/1)		0.002		0.010
		(0.029)		(0.029)
Household head engaged in non-farm		0.007		-0.005
		(0.030)		(0.032)
Total farm size (acre)		-0.001		-0.001
		(0.001)		(0.001)
Total number of plots managed		-0.032***		-0.034***
		(0.010)		(0.010)
Plot is rented or purchased		-0.039		-0.040
		(0.042)		(0.044)
Tenure system: customary		0.010		0.019
		(0.036)		(0.037)
Pure stand cropping		-0.026		-0.008
		(0.022)		(0.022)
Soil type: sandy or clay		-0.039		-0.035
		(0.026)		(0.025)
Soil color: red or brown		0.010		0.010
		(0.022)		(0.022)
Slope of plot: flat		0.018		0.004
		(0.023)		(0.024)
Soil quality: good or very good		0.046**		0.059***
		(0.020)		(0.020)
Soil texture: fine or very fine		0.015		0.017
		(0.025)		(0.025)
Constant	0.220***	0.219***	0.204***	0.204***
	(0.012)	(0.012)	(0.012)	(0.011)
Mean dependent variable	0.541	0.540	0.521	0.520
R^2	0.229	0.246	0.200	0.219
No. observations	1546	1535	1546	1535

Notes: These estimates come from a linear probability (LPM)/OLS regression characterizing round patterns. Rounding stands for a dummy variable assuming a value of 1 if self-reported values are 0.5, 1, 1.5, 2 acre and 0 otherwise. Rounding incorrectly assumes if self-reported values assume these rounded values and are different from GPS-based values, and 0 otherwise. Standard errors, clustered at enumeration area level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Characterizing measurement error in plot size (post-planting round only)

	(1)	(2)	(3)	(3)
	Log(SR)-log(GPS)		%Overestimation	%Underestimation
	OLS estimates	Shapley	Tobit estimates	Tobit estimates
Plot size		**78.72%**		
Log (area: GPS)-centered	-0.680***		-210.759***	37.617***
	(0.017)		(6.953)	(1.859)
Log (area: GPS)-centered-square	-0.014		11.307***	8.928***
	(0.011)		(4.097)	(1.039)
Rounding of values		**18.28%**		
Rounding at 0.5 acre	0.419***		120.048***	-19.058***
	(0.034)		(11.903)	(2.781)
Rounding at 1 acre	0.905***		270.761***	-58.441***
	(0.042)		(15.149)	(4.025)
Rounding at 1.5 acre	1.186***		354.823***	-81.165***
	(0.070)		(24.455)	(6.902)
Rounding at 2 acre	1.430***		401.143***	-92.946***
	(0.096)		(32.847)	(9.508)
Household characteristics		**1.69%**		
Female household head	0.025		14.033	2.040
	(0.044)		(16.624)	(3.986)
Log (household head)	0.039		3.394	-0.017
	(0.040)		(13.437)	(3.324)
Household head literate (0/1)	0.011		7.214	-2.364
	(0.033)		(11.205)	(2.762)
Household head married (0/1)	-0.016		15.065	-7.179*
	(0.014)		(17.011)	(4.081)
Household head Christian	0.007		-5.316	-1.948
(0/1)	(0.034)		(11.712)	(2.858)
Household head engaged in	-0.015		-19.620	-0.923
non-farm	(0.041)		(14.173)	(3.421)
Total farm size (acre)	0.003		0.360	-4.980***
	(0.004)		(1.122)	(1.497)
Total number of plots managed	-0.058***		-7.278**	5.498***
	(0.011)		(3.639)	(1.050)
Plot characteristics		**1.32%**		
Plot is rented or purchased	0.002		5.957	1.639
	(0.047)		(15.933)	(4.042)
Tenure system: customary	-0.112***		-35.406***	10.574***
	(0.039)		(12.950)	(3.418)
Pure stand cropping	0.064**		27.122***	-2.790
	(0.027)		(9.259)	(2.291)
Soil type: sandy or clay	0.035		12.542	-4.650**
	(0.028)		(9.428)	(2.307)
Soil color: red or brown	-0.010		-3.882	0.778
	(0.028)		(9.539)	(2.329)
Slope of plot: flat	-0.001		-0.074	-1.229
	(0.029)		(9.820)	(2.415)
Soil quality: good or very good	0.002		-3.820	0.652
	(0.027)		(9.363)	(2.289)

Soil texture: fine or very fine	-0.036		3.442	2.197
	(0.028)		(9.689)	(2.366)
Constant	0.006		-94.661*	-11.636
	(0.160)		(55.243)	(13.848)
Mean dependent variable	0.313		96.248	10.423
R^2	0.548	100%	0.480	0.294
No observations	1535		1535	1535
No. censored observations	-		554	1035

Notes: The first column provides OLS estimates, and the second column reports Shapley decomposition associated with the R^2 in the first column. The third and fourth columns are Tobit estimates. Household characteristics include the head, age, literacy, religion, marital status and non-farm work status of the household head, as well as total farm size and number of plots managed. Plot characteristics include indicator variables for tenure status, rental or owned, pure stand cropping, soil type, and slope. Standard errors, clustered at enumeration area level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Information spillovers on self-reporting of early season fertilizer application (with additional triple interactions)

	Fertilizer applied (yes=1, no=0) (1)		ln (fertilizer/acre)	
Treatment (yes = 1, no = 0)	0.198	0.100	-0.298*	-0.281*
	(0.464)	(0.452)	(0.178)	(0.163)
ln(plot size)	0.220***	0.231***	-0.249	-0.238
	(0.072)	(0.069)	(0.235)	(0.148)
Treatment • ln(plot size)	-0.046	-0.060	-0.192*	-0.226**
	(0.094)	(0.090)	(0.102)	(0.107)
SR overestimated (yes = 1, no = 0)	0.139	0.148		
	(0.371)	(0.360)		
Treatment • SR overestimated	-0.381	-0.325		
	(0.453)	(0.443)		
SR underestimate (yes = 1, no = 0)	0.145	0.201		
	(0.385)	(0.376)		
Treatment •SR underestimated	-0.297	-0.303		
	(0.475)	(0.471)		
% SR overestimate			0.001**	0.001**
			(0.001)	(0.001)
Treatment • % SR overestimate			-0.001	-0.001
			(0.001)	(0.001)
% SR overestimate x Plot size			0.000	0.000
			(0.000)	(0.000)
Treatment x % SR overestimate x Plot size			0.000	0.000
			(0.000)	(0.000)
% SR underestimate			-0.006**	-0.006**
			(0.002)	(0.002)
Treatment • % SR underestimate			0.002	0.004
			(0.004)	(0.004)
% SR underestimate x Plot size			-0.000	-0.000
			(0.002)	(0.002)
Treatment x % SR underestimate x Plot size			0.001	-0.000
			(0.003)	(0.003)
$\widehat{IMR}$			-0.274	-0.406
			(1.825)	(1.164)
Controls	No	Yes	No	Yes
Mean of dependent variable	0.674	0.674	4.242	4.244
R-squared			0.178	0.195
No. observations	1546	1535	1042	1034

Notes: All plot sizes are natural logarithms of GPS measures, demeaned to center the data. SR indicates self-reported data. % over-/under-estimate is computed as percentage difference between self-reported and GPS measures for values above zero and zero otherwise. IMR is the inverse Mills ratio from the first-stage probit of fertilizer application. Fertilizer application includes only fertilizer applications before or during planting. Standard errors, clustered at enumeration area level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Impact of information provision on reporting of early season labor application (with additional triple interactions)

	(1) Log (total labor, labor days/acre)	(2) Log(total labor, labor days /acre)	(3) Log(household labor, labor days /acre)	(4) Log(household labor, labor days /acre)
Treatment (yes = 1, no = 0)	0.022	-0.018	-0.006	-0.028
	(0.052)	(0.059)	(0.058)	(0.067)
ln(plot size)	-0.323***	-0.303***	-0.345***	-0.336***
	(0.041)	(0.043)	(0.043)	(0.046)
Treatment • ln(plot size)	-0.095	-0.080	-0.104*	-0.084
	(0.059)	(0.063)	(0.061)	(0.065)
% SR overestimate	0.001***	0.002***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Treatment • % SR overestimate	-0.001***	-0.001**	-0.001***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.001)
% SR overestimate x Plot size		0.000		0.000
		(0.000)		(0.000)
Treatment x % SR overestimate x Plot size		-0.000		-0.000
		(0.000)		(0.000)
% SR underestimate	-0.005**	-0.003	-0.005**	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)
Treatment • % SR underestimate	-0.002	-0.003	-0.001	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)
% SR underestimate x Plot size		-0.002		-0.001
		(0.002)		(0.002)
Treatment x % SR underestimate x Plot size		0.002		0.001
		(0.003)		(0.003)
Constant	4.205***	4.286***	4.106***	4.197***
	(0.043)	(0.152)	(0.047)	(0.149)
Controls	No	Yes	No	Yes
Mean of dependent variable	4.216	4.223	4.099	4.106
R-squared	0.269	0.299	0.250	0.278
No. observations	1540	1529	1538	1527

Notes: All plot sizes are natural logarithms of GPS measures, demeaned to center the data. SR indicates self-reported data. % over-/under-estimate is computed as percentage difference between self-reported and GPS measures for values above zero and zero otherwise. That is, for each over(under)estimated plot we compute percentage difference between self-reported and objective measures. Labor application includes labor allocations before or during planting (for land preparation, planting and ridging). Standard errors, clustered at enumeration area level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Bidirectional measurement error in plot size and the impact of information provision (restricting the sample to the same respondent)

	(1)	(2)	(3)
	Measurement error: Post-harvest [log(self-reported)-log(GPS)]		
Treatment	0.061**	0.066**	0.071**
	(0.026)	(0.029)	(0.029)
Plot size	-0.000	-0.000	-0.002
	(0.000)	(0.000)	(0.007)
Treatment x Plot size	-0.330***	-0.329***	-0.326***
	(0.044)	(0.043)	(0.046)
Measurement error-pre-treatment	1.000***	1.000***	0.996***
	(0.000)	(0.000)	(0.006)
Treatment x Measurement error-pre-treatment	-0.784***	-0.778***	-0.777***
	(0.076)	(0.077)	(0.074)
Measurement error-pre-treatment x Plot size		-0.000	-0.001
		(0.000)	(0.004)
Treatment x Measurement error-pre-treatment x plot size		0.011	0.012
		(0.047)	(0.047)
Constant term	0.310***	0.310***	0.333***
	(0.000)	(0.000)	(0.106)
Controls	No	No	Yes
Mean of dependent variable	0.335	0.335	0.339
R-squared	0.675	0.675	0.677
No. observations	1315	1315	1305

Notes: Measurement error is computed as between log-transformed self-reported and GPS values, log(self-reported)-log(GPS). Standard errors, clustered at enumeration area level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Measurement error in plot size and the impact of information provision: Tobit estimates (restricting the sample to the same respondent)

	(1)	(2)	(3)	(4)	(5)	(6)
	%Overestimation: Post harvest			**%Underestimation: Post harvest**		
Treatment	9.114	-18.498	-19.958	-2.075	-2.002	-2.120
	(11.499)	(14.270)	(14.722)	(2.037)	(2.033)	(2.096)
Plot size	-20.547***	-15.466***	-12.377**	5.148***	7.565***	7.811***
	(5.425)	(5.768)	(6.286)	(1.051)	(1.238)	(1.364)
Treatment x Plot size	-92.155***	-101.733***	-104.511***	2.488	-0.520	-0.407
	(13.900)	(15.211)	(15.401)	(2.085)	(2.044)	(2.151)
% SR overestimate pre-treatment	1.141***	1.394***	1.384***			
	(0.032)	(0.065)	(0.068)			
Treatment x % SR overestimate	-0.700***	-1.148***	-1.133***			
	(0.148)	(0.195)	(0.189)			
% SR overestimate x Plot size		0.181***	0.172***			
		(0.029)	(0.029)			
Treatment x % SR overestimate x Plot size		-0.326***	-0.318***			
		(0.103)	(0.102)			
% SR underestimate pre-treatment				1.526***	1.607***	1.611***
				(0.071)	(0.075)	(0.080)
Treatment x % SR underestimate				-1.131***	-1.247***	-1.258***
				(0.120)	(0.125)	(0.128)
% SR underestimate x Plot size					-0.191***	-0.196***
					(0.046)	(0.047)
Treatment x % SR underestimate x Plot size					0.295***	0.292***
					(0.085)	(0.082)
Constant	36.526***	52.290***	96.971***	-10.639***	-10.807***	-6.521
	(7.606)	(6.695)	(32.006)	(2.562)	(2.510)	(5.973)
Control	No	No	Yes	No	No	Yes
Mean of dependent variable	95.116	95.116	95.616	8.110	8.110	7.982
Log-likelihood value	-5501.739	-5487.039	-5443.583	-2080.502	-2071.435	-2040.778
No. observations	1315	1315	1305	1315	1315	1305

Notes: These results represent Tobit estimates characterizing over and underestimation rates. Overestimation and underestimation rates are computed as percentage difference between self-reported and GPS measures for values above zero and zero otherwise. Standard errors, clustered at enumeration area level, given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Impact of information provision on reporting of early season fertilizer application (restricting the sample to the same respondent)

	ln (fertilizer/acre)		
	(1)	(2)	(3)
Treatment (yes = 1, no = 0)	-0.351***	-0.361***	-0.362***
	(0.065)	(0.065)	(0.068)
ln(plot size)	-0.346***	-0.203***	-0.196***
	(0.046)	(0.058)	(0.059)
Treatment • ln(plot size)	-0.084	-0.221***	-0.245***
	(0.064)	(0.080)	(0.081)
% SR overestimate		0.001***	0.001***
		(0.000)	(0.000)
Treatment • % SR overestimate		-0.001**	-0.001***
		(0.001)	(0.001)
% SR underestimate		-0.007***	-0.007***
		(0.003)	(0.003)
Treatment • % SR underestimate		0.002	0.003
		(0.004)	(0.004)
Controls	No	No	Yes
Mean of dependent variable	4.248	4.248	4.250
R-squared	0.166	0.186	0.211
No. observations	894	894	886

Notes: All plot sizes are natural logarithms of GPS measures, demeaned to center the data. SR indicates self-reported data. % over-/under-estimate is computed as percentage difference between self-reported and GPS measures for values above zero and zero otherwise. That is, for each over(under)estimated plot we compute percentage difference between self-reported and objective measures. Fertilizer application includes only fertilizer applications before or during planting. Standard errors, clustered at enumeration area level, given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Impact of information provision on reporting of early season labor application (restricting the sample to the same respondent)

	(1) Log (total labor, labor days /acre)	(2) Log(total labor, labor days /acre)	(3) Log(household labor, labor days /acre)	(4) Log(household labor, labor days /acre)
Treatment (yes = 1, no = 0)	0.033	0.014	0.005	0.002
	(0.046)	(0.047)	(0.050)	(0.051)
ln(plot size)	-0.323***	-0.320***	-0.345***	-0.348***
	(0.042)	(0.042)	(0.046)	(0.046)
Treatment • ln(plot size)	-0.070	-0.054	-0.081	-0.062
	(0.056)	(0.056)	(0.061)	(0.060)
% SR overestimate	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Treatment • % SR overestimate	-0.001*	-0.001*	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
% SR underestimate	-0.005**	-0.005**	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Treatment • % SR underestimate	-0.002	-0.002	-0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Controls	No	Yes	No	Yes
Mean of dependent variable	4.210	4.218	4.094	4.102
R-squared	0.271	0.297	0.252	0.279
No. observations	1309	1299	1307	1297

Notes: All plot sizes are natural logarithms of GPS measures, demeaned to center the data. SR indicates self-reported data. % over-/under-estimate is computed as percentage difference between self-reported and GPS measures for values above zero and zero otherwise. That is, for each over(under)estimated plot we compute percentage difference between self-reported and objective measures. Labor application includes labor allocations before or during planting (for land preparation, planting and ridging). Standard errors, clustered at enumeration area level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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