Close to the Edge: High Productivity at Plot Peripheries and the Inverse Size-Productivity Relationship

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Smaller farms and plots are more productive per hectare than larger ones. Some researchers hypothesize that it reflects household-specific shadow prices; others reject the relationship as spurious, invoking measurement error or omitted variables. Using unique, plot-level panel data from Uganda, we estimate the inverse size-productivity relationship and generate three important findings. First, the standard inverse relationship is a plot-level phenomenon, rendering conventional household- or farm-level explanations insufficient. Second, the plot perimeter/area ratio, reflecting an "edge effect" discussed in the agronomy literature wherein productivity is highest around the periphery of plots, explains most or all of the inverse plot size-productivity relationship. Third, we present suggestive evidence consistent with behavioral and biophysical mechanisms underpinning the edge effect.

Keywords: inverse relationship, productivity, behavioral, causal bounds, perceptions, edge effect

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1 Introduction

It has long been observed that smaller farms produce more per unit area than larger farms, ceteris paribus, across a number of developing and non-developing settings. This has been observed in Africa (Collier, 1983; Van Zyl, Binswanger and Thirtle, 1995; Barrett, 1996; Kimhi, 2006; Barrett, Bellemare and Hou, 2010; Carletto, Savastano and Zezza, 2013; Larson et al., 2014), in Asia (Sen, 1962; Mazumdar, 1965; Bardhan, 1973; Carter, 1984; Heltberg, 1998; Akram-Lodhi, 2001; Benjamin and Brandt, 2002; Rios and Shively, 2005), in Europe (Alvarez and Arias, 2004) and in Latin America (Berry and Cline, 1979; Kagin, Taylor and Yúnez-Naude, 2015), to cite only a few studies. Of course, textbook neoclassical theory predicts equal marginal factor productivity across production units, else high marginal productivity users should purchase or rent land from low productivity users at a mutually attractive price, thereby increasing aggregate output and equalizing marginal returns. The existence of any relationship between farm productivity and farm size, either negative or positive, has therefore attracted much attention from development and agricultural economists as an important puzzle to resolve, because it suggests Pareto inefficient resource allocation.

How one explains the puzzle — the mechanism(s) that one hypothesizes generate the inverse size-productivity relationship — serves as a metaphor for how one understands the development challenge in low-income agrarian societies. Potential explanations therefore have important, practical implications. For example, if small farms are inherently more efficient in a given setting, redistributive land reform should be a source of both equity and efficiency gains. If market failures create household-specific shadow prices that drive the inverse relationship, then the fundamental welfare theorems of neoclassical economics may not hold, meaning competitive markets do not yield Pareto optimal distributions and government interventions may be necessary. Conversely, if the inverse relationship is purely a statistical artifact attributable to measurement error or to omitted relevant variables, then the rural economy may function as predicted by Walrasian theory and interventions may generally prove inefficient.

So how one understands the inverse size-productivity puzzle matters.

Using plot-level panel data from rural Uganda we demonstrate that the inverse relationship exists at the plot level within farms, not only at the farm level. We also provide highly suggestive evidence of causality, for the first time in this literature to the best of our knowledge. We test the familiar explanations and find that they fail to explain the observed inverse relationship in these data. We next propose and examine a new mechanism that appears to explain much of the inverse relationship in our data: higher marginal productivity within plot peripheries — the "edge effect" — drives smaller plots to be more productive than larger plots, as a larger share of small plot area falls along the plot's perimeter. While we are unable to identify whether behavioral or biophysical factors drive the apparent edge effect, we do find that farmers apply more labor around more visible and accessible plot edges.

Two classes of mechanisms are most commonly hypothesized to drive the inverse relationship. Chayanov (1991) first observed that Russian peasant farmers were more productive than larger farmers, and hypothesized that their propensity to employ massive quantities of family labor in the farming enterprise explained this differential.[1] In seminal papers, Sen (1966) and Feder (1985) develop this Chayanovian hypothesis, theorizing that labor market failures drive high shadow prices for labor for larger farmers, who are unable to efficiently hire and/or supervise workers; these farm-specific shadow prices drive the inverse relationship. Barrett (1996) builds on this by showing that even in the absence of labor market failures, multiple market failures may cause smaller farmers to apply more labor per hectare, and hence be more productive. Kagin, Taylor and Yúnez-Naude (2015) illustrate that smallholder farmers in Mexico are more technically efficient, as well as more productive, than their larger counterparts.

By contrast, a different thread of literature explains the observed inverse size-productivity relationship as illusory, a mere statistical artifact rather than a causal relationship. This could result from measurement error around farm size generating a spurious correlation (Lamb, 2003). It might also result from omitted relevant variables bias if farm size is endogenous to soil quality, with more fertile soils inducing both higher yields and denser settlement patterns leading to smaller farms (Bhalla and Roy, 1988; Benjamin, 1995; Assunção and Braido, 2007).

Resolution of the puzzle has long been complicated by the fact that few if any previous datasets were suited to provide well-identified, causal estimates of the inverse relationship. The size of a farm or even of a specific plot within a farm will almost surely be correlated with many unobserved factors. Nonetheless, a few recent studies examine household panel data or rich, plot-level data to provide evidence that neither multiple market failures nor measurement error/omitted variables drive the inverse relationship, thereby intensifying the puzzle.

Authors using household level panel data find that the inverse relationship between farm size and farm productivity persists even when household fixed effects control for the time-invariant component of household-specific shadow prices (Henderson, 2015; Kagin, Taylor and Yúnez-Naude, 2015). They cannot, however, rule out time-varying shadow prices, correlated with farm size, as driving the relationship. If some households enter or exit local factor markets across survey rounds their shadow prices should shift (Carter and Yao, 2002). Authors using household fixed effects in plot-level data find that the inverse relationship remains and is often stronger at the plot level than at the farm level (Assunção and Braido, 2007; Barrett, Bellemare and Hou, 2010; Ali and Deininger, 2015). These findings even more strongly indicate that household-specific shadow prices are not driving the inverse relationship. It nonetheless remains possible that plot-level shadow prices or omitted variables drive the relationship. Jointly, these household panel and plot-level studies seem to rule out multiple market failures as a full explanation of the phenomenon.

The statistical artifact hypothesis has not stood up well to recent empirical tests either. Barrett, Bellemare and Hou (2010) use cross-sectional, plot-level data from Madagascar with soil quality measurements to show that including controls for soil biochemical and physical properties does not explain the inverse relationship in their context. Similarly, Carletto, Savastano and Zezza (2013) show that the inverse relationship actually

[1] Chayanov's book was published in English in 1991, "The Theory of Peasant Cooperatives." His original text was published in Moscow in 1921, "Osnovnye idei i formy organizatsii sel'skokhozyaistvennoi kooperatsii" (The basic ideas and organizational forms of agricultural cooperation).

increases in magnitude when farm size is based on plot-specific GPS measures rather than farmer estimates that may be subject to considerable measurement error. In their data, Ugandan smallholders with small farms tend to over-report plot size while larger farmers tend to under-report plot size, so removing measurement error around plot size actually reinforces rather than explains away the inverse relationship. Carletto, Gourlay and Winters (2015) show the same using data from Malawi, Uganda, Tanzania and Niger.

Two new papers examine a new statistical artifact hypothesis — that farmers may systematically over-estimate production on smaller plots and under-estimate it on larger plots. Using a two round household panel in a district of Eastern Uganda, Gourlay, Kilic and Lobell (2017) estimate the inverse relationship using conventional, farmer-recalled measures of crop yield, but find no inverse relationship when yields are measured via crop cutting. Desiere and Jolliffe (2017) find the same when comparing farmer-recalled yield and yields derived from crop cuts. In both papers, the difference between recalled yields and cut-calculated yields is inversely related to plot size. If cut-calculated yields are closer to "true" yields than are farmer-estimated yields, the inverse relationship may be driven by systematic patterns in farmer recall error. If crop cuts over-estimate yield on larger plots and under-estimate yields on smaller plots, however, the disappearance rather than existence of the inverse relationship may be the statistical artifact.

So almost one hundred years after Chayanov first drew attention to this puzzle, it remains important and unresolved in the literature. The mechanisms previously considered most promising — the multiple markets failures and statistical artifact hypotheses — have not held up to recent, rigorous analyses. Additionally, while it is increasingly clear that the inverse relationship lies at least in part at the plot level, plot size is correlated with unobserved factors such as distance to home, crops planted, or input intensity (Tittonell et al., 2007, 2005). Thus, in the absence of random or quasi-random variation in plot size, the causal mechanism remains unclear.

We address these important gaps in knowledge primarily by using plot-level, geospatially- matched panel data to estimate the inverse relationship.[2] While the most recent literature seems to have ruled out household-level shadow prices as driving the inverse relationship, no evidence attests to the role of plot-level shadow prices. Because plot shape and plot size vary over time (along with other plot-level characteristics), plot-level fixed effects allow us to estimate the inverse relationship while simultaneously controlling for time-invariant plot characteristics such as location within the landscape, distance to road or household, slope, elevation, and other factors that might affect plot-specific shadow prices of inputs and outputs.

We also estimate all results in a larger, pooled dataset of plot-level observations from both survey rounds, using household-time fixed effects as did Assunção and Braido (2007). The fact that this estimation method (identifying on within household-time, across-plot variation) and the plot fixed effect estimation method (identifying on within-plot, over-time variation) recover almost identical inverse relationship estimates suggests that plot size is causally associated with plot productivity. That is, in the pooled setting, only within-time-period, across-plot shadow prices or unobserved

[2]To the best of our knowledge, this is the first paper to use plot-level panel data for this purpose.

variables might bias estimation of the relationship. Yet in the geospatially-matched panel setting we can control for all time-invariant plot characteristics, such that only time-varying shadow prices or unobserved variables might bias estimation, and we find the same relationship. This suggests that the inverse relationship is either causal, or biased by omitted variables that change across plots within households in precisely the way that they change within plots across time, which seems rather unlikely.

Our contribution to the literature is therefore three-fold. First, we validate recent findings indicating that household shadow prices play little or no role in driving the inverse relationship, which occurs at the plot level. We do this both by comparing the predictive value of farm size to the predictive value of plot size, and by comparing the inverse relationships estimated under various identification strategies. We additionally validate that neither measurement error around plot size, nor soil fertility, nor other oft-omitted, plot-specific characteristics drive the relationship. The conventional, contending hypotheses — multiple markets failures versus statistical artifact — do not seem to explain the puzzle in our data, as with other recent studies.

Second, we provide evidence that plot size is causally associated with plot productivity. We do this implicitly when comparing the inverse relationship estimated under household-time fixed effects and plot fixed effects. Additionally, thinking of causality in a more classic light, we acknowledge that plot size is not exogenous to all time-varying plot characteristics and use a technique proposed by Oster (2016) to calculate bounds around the probable, causal effect of plot size on plot productivity. The estimated causal bounds fit so tightly around the original estimate that under any plausible assumption, omitted relevant variables attenuate the inverse relationship by only five percent. This exercise suggests that the inverse relationship is both causal and large in magnitude.

Third, we propose and explore a new mechanism behind the inverse relationship, one rooted in more recent observations of the importance of both behavioral phenomena and biophysical constraints in explaining economic puzzles. A sizable agronomy literature documents the existence of an "edge effect" wherein the peripheral rows of a plot are more productive than interior rows within a plot (Little and Hills, 1978; Barchia and Cooper, 1996). For instance, Verdelli, Acciaresi and Leguizamón (2012) found that the outer rows of corn in Argentinian corn and bean plots yielded 35-46 percent more than the center rows. In Illinois, border row corn yields were 37 percent higher than those of interior rows (Ward, Roe and Batte, 2016). Holman and Bednarz (2001) find that cotton at the very edge of plots yields 360 percent more than cotton at the interior.

These agronomic experimental results suggest that the peripheral area of a plot may experience higher yields for biophysical reasons due to increased sunlight exposure (Barchia and Cooper, 1996), differences in pests, biodiversity or pollination (Balagawi, Jackson and Clarke, 2014), greater nutrient uptake due to reduced competition (Watson and French, 1971) or greater water availability (O'Brien and Green, 1974). There might also be behavioral mechanisms if the plot periphery is more visible or more accessible to a farmer in such a way that it changes her awareness and thus management of the plot. Behavioral economics research illustrates, for example, that individuals change food consumption behavior based on information about portion size or based on visual cues about portion size (Just and Wansink, 2014; Wansink, Painter and North, 2005). We might similarly hypothesize that farmers change crop or soil management based on visual signals of crop growth conditions. Farmers can see weed growth, pest infestation, plant disease or other yield-dampening phenomena more readily on a plot's perimeter than within its interior and can often reach the perimeter more easily as well.

For both behavioral and biophysical mechanisms, the edge effect should vary by crop type, cropping system, plot lay-out, border direction, and likely many other factors. For instance, reviewing a couple decades of literature, Ward, Roe and Batte (2016) suggest that the edge effect is stronger in intercropped systems (common in Uganda and sub-Saharan Africa more generally) than in mono-cropped systems. Additionally, row orientation and border direction also impact the edge effect, with northern-facing border rows often having the largest productivity differential, and north-south oriented rows mitigating the edge effect Barchia and Cooper (1996). Almost certainly the properties of adjacent plots will matter. The edge effect may be larger for a plot bordering ground crops, for instance, than for a plot bordering sunlight-blocking tree crops. If farmer behavior drives the edge effect, it may be greater for plots closer to the house, or for plots with higher-value crops.

If plot perimeters are on average more productive than plot interiors, for whatever reason(s), then smaller plots with larger perimeter/area ratios will be more productive on average than larger plots, plausibly driving part or all of the oft-observed inverse relationship. In our data, controlling for the edge effect using the perimeter-area ratio explains most or all of the inverse size-productivity relationship. Therefore, in these data at least, the inverse relationship seems strongly associated with edge effects, i.e., by either differential unobserved biophysical inputs at the periphery of plots, or differential input allocation responding endogenously to behavioral cues.[3] We cannot parse what is essentially an average treatment effect for a likely heterogeneous process. But no matter the cause of the edge effect, differential input application rates lead to real inefficiency, as opposed to a mere statistical illusion.

Having established the importance of the edge effect, we explore both biophysical and behavioral phenomenon, finding stronger support for behavioral explanations. These are, however, merely suggestive findings, in part because we cannot entirely untangle the biophysical and behavioral drivers of the edge effect. We show that labor per hectare rises with perimeter/area ratio, and also that this effect is only significant for family (non-hired) laborers, who may be more assiduous in tending the highly-visible perimeter of a plot. We also show that when a farmer over-estimates a plot's size, she tends to over-allocate inputs to the plot, which then becomes more productive. Similarly, under-estimation of plot size appears to lower plot productivity due to under-allocation of inputs. Because plot size misperceptions are purely cognitive errors, a farmer's awareness of and thus beliefs about space may change her management practices, and thus could plausibly drive plot productivity.

[3]It is worth noting that we have only farmer-recalled yield data, and so cannot compare our results to those obtained using yields calculated from crop cuts, as do Gourlay, Kilic and Lobell (2017) and Desiere and Jolliffe (2017). However, if the edge effect drives the inverse relationship, yields based on crop cuts will generally fail to capture the phenomenon anyway, as crop cuts are taken in the plot interior and therefore representative only of interior productivity. (Though it is true that for a small subset of fully harvested plots, Gourlay, Kilic and Lobell (2017) find the same disappearance of the inverse relationship; in this context farmers may truly be systematically over-estimating yields on smaller plots.)

2 Data

We use plot-level panel data from rural Uganda. The first wave of data was collected during the summer of 2003, by the International Food Policy Research Institute (IFPRI). This IFPRI survey was run in conjunction with a larger Uganda Bureau of Statistics (UBOS) survey conducted in 2002/2003. Together, the surveys collected household-level socioeconomic data, plot-level input and production data, and took plot-level soil samples for later soil analysis. Additionally, farmers estimated the size of each of their plots, and plot perimeter, plot size and plot centroid were measured via GPS. (See Appendix 1 for details on plot size calculations.) Information on the sampling strategy used in 2003 can be found in Nkonya et al. (2008).[4]

The second wave of data was collected during the summer of 2013 under a National Science Foundation (NSF) funded project. The same household- and plot-level data were collected, along with plot-level soil samples. Of the 859 households interviewed in 2003, 803 were tracked successfully and re-interviewed. Additionally, individuals who had split off from the original 2003 household to form a new household were tracked if they were still within the original parish. Appendix 2 examines attrition — households that attritted tended to live in peri-urban areas and on average were slightly younger, slightly smaller, slightly more educated and had slightly less land and fewer animals.

In each wave, soil samples were aggregated from 12-20 subsamples (based on plot size) taken in a zig-zag pattern across each plot. Samples were then analyzed for a number of biophysical and chemical characteristics at the National Agricultural Research Laboratory in Uganda using well-established protocols. Details on the soil sampling strategy as well as soil analysis can be found in Appendix 3.

In this paper, the unit of analysis is a single plot of land, used to grow a single crop or multiple, mixed crops. Most, though not all, farmers have multiple plots in both 2003 and 2013.[5] While the size and shape of these plots shifts across the decade, many of them are generally in the same location within a larger parcel/unit of land. Because GPS waypoints were taken around the corners of all plots in both rounds of data collection, we can match plots across rounds using their geospatial location. This is how we form a plot-level panel dataset — our primary dataset. (More details on the geospatial matching process can be found in Appendix 1.) Additionally, we pool all plots from both rounds into one dataset, which constitutes our second, pooled dataset used for analysis without plot fixed effects.[6]

Because most of Uganda has two agricultural seasons, agricultural input and production data were gathered for both seasons. We therefore consider four time periods, one for

[4]Essentially, rural households were randomly chosen within survey districts, but the survey districts themselves were chosen to represent various agro-ecological zones across Uganda. Thus, the results in this paper cannot be viewed as representative across Uganda.

[5]In 2003 and 2013, 16% and 32% percent of households, respectively had only 1 plot. Thus, 5.3% and 14.0% of plots belonged to a single-plot household in 2003 and 2013, respectively.

[6]Of the 2,549 plots recorded in the 2003 survey, 25 percent (631) were geospatially matched. Of the 1,773 plots recorded in the 2013 survey, 42 percent (738) were geospatially matched. We therefore have 738 plots in our plot panel dataset, each viewed in 2-4 agricultural seasons (but necessarily at least 1 agricultural season per round), totaling 2,182 observations. We have 4,322 plots in our pooled dataset, each viewed in 1-2 agricultural seasons within their respective round, totaling at 6,704 observations.

each agricultural season of each round. Plot size and shape do not vary across season within round, but other plot-level characteristics such as as fertilizer use, organic amendment or management do. Plot productivity (revenue per hectare) also varies across all four time periods. To be included in the plot-level panel, a plot must be viewed in each round. Not all plots were farmed in both seasons, however. Our panel is therefore unbalanced, with plots viewed 2-4 times, depending on how many seasons they were farmed.

Table 1 summarizes all key variables used in analysis, for 2003 and 2013, for our plot-level panel dataset. (Appendix 4 summarizes the same variables for our pooled dataset.) Both plots and farms are shrinking over time, and at a similar rate — in 2013 the median area for either unit is about 60 percent of the median area in 2003. Plots are also far more productive (measured in terms of revenue per hectare) in 2013 than in 2003, and labor intensity (hours/hectare/day) far higher. Soil became slightly more acidic over the decade, while organic carbon content appears to have slightly increased.[7]

Inputs, management and cropping systems also shifted slightly over the decade. Organic amendment (manure, crop residue, food residue or compost) is less likely to be applied in 2013 than in 2003. Terracing is less commonly practiced in 2013 while crop rotation is more commonly practiced. In both years the use of inorganic fertilizer is negligible, as is the use of irrigation; less than 2 percent of plots benefit from either practice in either year. Household heads appear to own and manage plots at slightly higher rates in 2013. In both years, about 50 percent of plots are under a mixed cropping system, i.e., hold multiple crops. Intercropping, defined more strictly as alternating rows of different crops, rises in prevalence between 2003 and 2013. Yet the number of plots holding each crop category (tubers, legumes, bananas, cereals and cash crops) declines between 2003 and 2013, due to a decline in the average number of crops grown per household (see Tables A10 and A12) as well as a decline in the average number of crops grown per plot.

In our primary analysis, the inverse relationship is driven by within-plot change in size over time (controlling for year and season fixed effects). Appendix 5 holds detailed information on the determinants of this plot size change. Thirty-two percent of plots grow over the decade while 68 percent of plots shrink over the decade. These changes in size are not random: the primary predictor of plot size change is 2003 plot size. Larger plots are both more likely to shrink and they shrink more, on average. Plots are also more likely to shrink if they are located on parcels of land that have been subdivided between 2003 and 2013. Generally, however, these are the larger plots, and starting plot size has more explanatory power than parcel division, when it comes to predicting changes in size across all plots.[8]

There is, of course, a selection process into the geospatially matched panel dataset. Some plots cannot be matched over time, as they have no geospatial overlap with

[7]This change in organic carbon content may be due to a slight change in analysis technique rather than a true change in content. In both years, soil organic matter was obtained via the Walkley-Black test. However, the buffer pH changed across years, potentially causing more organic matter to be extracted from samples in the 2013 test. Because round fixed effects are used in all analysis, this mean shift should have no consequence for our results.

[8]The vast majority of geospatially matched plots, all but 16, remain under the same ownership over the decade. Changes in ownership are not driving plot size or productivity changes.

another plot from across the decade. We drop these plots from our analysis. Some 2003 plots are matched to multiple 2013 plots, generally because they have been split up into smaller plots over the decade.[9]

Because this selection process may not be random, Appendix 6 compares household and plot characteristics in the plot panel dataset to household and plot characteristics in the larger universe of all pooled plots from 2003 and 2013. While household characteristics differ only slightly across the two datasets, plot characteristics differ substantially — plots in the panel dataset are larger, receive less labor per hectare, are more likely to grow bananas or cash crops, are less likely to be rotated and are more likely to receive organic amendment. These plots cannot, therefore, be viewed as representative of the larger universe of plots in our pooled data.

Therefore, we also estimate all core results under household-time (specifically, household-year-season) fixed effects. Plots within the household-time fixed effects analysis *can* be viewed as representative of the larger universe of plots (also shown in Appendix 6).[10] If coefficients estimated under plot fixed effects are similar to those estimated household-time fixed effects, this suggests unbiasedness; it is unlikely that two separate selection mechanisms would drive/bias coefficients in an identical fashion.

3 Estimation Strategy

3.1 Shadow Prices (Plot vs. Household Mechanisms)

We first estimate the inverse size-productivity ratio according to farm size, plot size, and under various fixed effects models, in order to investigate whether household-level shadow prices drive the inverse relationship, as much of the literature has long held. Let Y_{ijt} be the productivity of plot j within farm i in time period t, where productivity is defined as revenue per hectare and t takes a unique value for each year-season combination.[11] (Uganda has two agricultural seasons.) Plot area is given by A_{ijt}, and farm size is given by A_{it}. [12]

The inverse relationship can be estimated including only A_{ijt}, including only A_{it}, or including both area measures. The inverse relationship will appear as a negative and statistically significant coefficient estimate on farm size, plot size, or both. These

[9]Of the 631 plots from 2003 that were geospatially matched to a 2013 plot, 70 percent were matched to exactly 1 plot from 2013, 20 percent were matched to 2 plots, 7 percent were matched to 3 plots, 2 percent were matched to 4 plots, and an additional 1 percent were matched to 5-9 plots. In only 16 cases (1.8 percent of the plots in our panel) was part of a 2003 plot split off and under new management in 2013. (Generally the plot was inherited by a child.) No other plots change ownership. More details can be found in Appendix 1.

[10]This is despite the fact that households with only one plot are dropped from household-time fixed effect analysis. Household characteristics do change slightly in this smaller dataset, relative to the larger pooled dataset, but time-invariant household characteristics are partialled out in both types of analysis.

[11]Because a variety of crops are being grown across and within plots, productivity cannot be measured solely as physical yields.

[12]At this point, let plot area be measured by GPS. In the next sub-section GPS measurement is compared to farmer-recalled plot size. Farm area is given by aggregated plot area, using GPS-measured plot size when available and farmer-recalled plot size for those plots that were not visited by an enumerator.

relationships can be estimated using simple Ordinary Least Squares (OLS) with no fixed effects as in Equation 1. The relationship with plot size can additionally be estimated by including household-time fixed effects λ_{it} as in Equation 2. (Farm size can no longer be included, as it only varies by household and time.) And both relationships can be estimated by including plot fixed effects λ_{ij} and a time fixed effect λ_t as in Equation 3.

$$Y_{ijt} = \delta_1 A_{it} + \gamma_1 A_{ijt} + \varepsilon_{ijt} \tag{1}$$

$$Y_{ijt} = \gamma_2 A_{ijt} + \lambda_{it} + \varepsilon_{ijt} \tag{2}$$

$$Y_{ijt} = \delta_3 A_{it} + \gamma_3 A_{ijt} + \lambda_{ij} + \lambda_t + \varepsilon_{ijt} \tag{3}$$

If $\hat{\gamma_1}$ is significant and negative once A_{it} is controlled for in Equation 1, the inverse relationship must stem at least in part from phenomenon at the plot, rather than household, level. If household-level shadow prices drive the inverse relationship, then the plot-level relationship should disappear once household-time fixed effects are controlled for in Equation 2, or plot fixed effects are controlled for in Equation 3.

Because we find that the inverse relationship stems solely from plot-level, rather than household-level phenomenon (i.e., once A_{ijt} is controlled for, controlling for A_{it} offers no additional, statistically significant information), all future equations estimate γ_3 using plot and time fixed effects, as in Equation 2, but excluding A_{it}. This identification strategy, new to the inverse relationship literature, differences away all time-invariant, plot-specific shadow prices and/or characteristics that might drive the inverse relationship, related to features such as distance from the homestead, slope, or position on the toposequence. Only unobserved plot-level characteristics that vary across time with plot size may bias the estimated relationship in Equation 2.

We also, however, estimate all equations using household-time fixed effects as in Equation 2; these results appear in Appendix 4. This identification strategy controls for household-and-season-specific shadow prices and other household-level factors, both time invariant and time-varying, but allows for within-season plot-level unobservables to bias the relationship. Because these strategies identify the inverse relationship off different sources of variation, if the $\hat{\gamma_2}$ and $\hat{\gamma_3}$ estimates are statistically identical, it suggests that neither household-level nor plot-level factors are biasing the relationship — rather, plot size itself drives plot-level productivity. Otherwise, two different sources of bias must coincidentally result in the same parameter estimate.

3.2 Measurement Error

We then investigate how measurement error around plot size influences the estimated inverse relationship between plot size and productivity. Let Y^m_{ijt} be the productivity of plot j within farm i in time period t, where method m was used to measure the size of plot i. Method m may be either size reported by farmer or size measured via GPS. Similarly, let A^m_{ijt} be the area of plot i within household j, measured by method m.

$$Y^m_{ijt} = \gamma_4 A^m_{ijt} + \lambda_{ij} + \lambda_t + \varepsilon_{ijt} \tag{4}$$

If the inverse relationship is partly a statistical artifact driven by measurement error, then $\hat{\gamma_4}$ estimated under Equation 4 should be smaller in absolute value and R^2 should be smaller with the GPS plot size measure as compared to farmer recall. Alternatively, measurement error in farmer reporting of plot size might attenuate the $\hat{\gamma}_4$ estimate, as found by Carletto, Savastano and Zezza (2013).

3.3 Omitted Variables and Causality

We next consider the possibility of omitted variable bias. A number of plot characteristics shift between 2003 and 2013, as evidenced in Table 1. If some of these characteristics (soil quality, crops grown, etc.) change across rounds in a way that is related to changes in plot size and plot productivity, failing to control for them might cause a spuriously estimated inverse relationship.[13]

Equation 5 therefore controls for an exhaustive list of time-varying plot characteristics X_{ijt}, alongside plot size A_{ijt} from Equation 4, having identified the optimal plot size measure method m.

$$Y_{ijt} = \gamma_5 A_{ijt} + \beta X_{ijt} + \lambda_{ij} + \lambda_t + \varepsilon_{ijt} \tag{5}$$

We first allow X_{ijt} to encompass a set of plot-specific soil fertility indicators, in order to explore whether omitting soil quality from Equation 4 drives a spurious correlation between plot size and plot productivity, as has been hypothesized in the literature. We allow X_{ijt} to include time-varying plot characteristics relevant to plot productivity: agricultural inputs, plot ownership and management practices, and crops grown.

If the inverse relationship is robust to these controls, i.e., the coefficient estimate $\hat{\gamma}_5$ is stable with the introduction of relevant, but often omitted, variables X_{ijt}, then it is possible that the inverse relationship is at least partly causal, rather than merely reflecting omitted variable bias. Without further restrictive assumptions, however, it is impossible to quantify the likelihood of such causality.

Oster (2016), Krauth (2016) and Altonji, Elder and Taber (2005) develop a set of econometric techniques designed for this very purpose: to bound the causal effect of an endogenous explanatory variable under the threat of omitted relevant variable bias. The method uses restrictive though plausible assumptions regarding the relative correlations between a potentially endogenous explanatory variable (in our case, plot size) and relevant observables, and that variable and unobservables. We use the consistent estimator of bias derived by Oster (2016) to bound the true causal effect of A_{ijt} on Y_{ijt}.

Consider the data generating process $Y = \beta X + \psi w_1 + W_2 + \varepsilon$, where β gives the causal effect of the treatment variable X on the outcome Y, w_1 is an observable set of variables, and W_2 and the error ε are unobservable. Regressing Y on X alone results in the biased coefficient $\mathring{\beta}$ and R-squared $\mathring{R}$. Regressing Y on X and w_1 results in the (less) biased coefficient $\tilde{\beta}$ and R-squared $\tilde{R}$. The R-squared from a hypothetical but impossible regression of Y on X, w_1 and W_2 would result in R_{max}, a number which is less than 1 if measurement error or other factors prohibit the full explanation of Y.

[13]Similarly, if plot characteristics are correlated with size and productivity across plots within time, failing to control for them might also bias the estimated relationship under the household-time fixed effects specification.

Oster (2016) proves that with one key assumption,[14] the bias-adjusted coefficient estimate β^* can be approximated as below, and that β^* converges in probability to the true, causal coefficient β.[15] The parameter δ gives the relative proportion of X explained by unobservables vs. observables — so δ is always > 0, and if δ is $<$ (=)[>] 1, then X is more (equally) [less] influenced by observables than by unobservables.

$$\beta^*(R_{max}, \delta) = \tilde{\beta} - \delta\Big[\mathring{\beta} - \tilde{\beta}\Big]\frac{R_{max} - \tilde{R}}{\tilde{R} - \mathring{R}}$$

Equivalently, we calculate the bias-adjusted inverse relationship γ^* as in Equation 6, where R_4 is the R-squared obtained by estimating the univariate inverse relationship of Equation 4, and R_5 is the R-squared obtained by estimating the inverse relationship with a full set of controls as in Equation 5.

$$\gamma^*(R_{max}, \delta) = \hat{\gamma_5} - \delta\Big[\hat{\gamma_4} - \hat{\gamma_5}\Big]\frac{R_{max} - R_5}{R_5 - R_4} \tag{6}$$

The causal effect of X on Y will lie within the interval $\big[\tilde{\beta}, \beta^*(R_{max}, \delta)\big]$, and Oster (2016) suggests that in most situations the causal effect will lie within the bounds of $\big[\tilde{\beta}, \beta^*(min\{1.3\tilde{R}, 1\}, 1)\big]$. We calculate an equivalent bounding interval for the inverse relationship, $\big[\hat{\gamma_5}, \gamma^*(min\{1.3R_5, 1\}, 1)\big]$, and additionally calculate bounding intervals under even more restrictive R_{max} and δ parameters.

3.4 The Edge Effect

We next propose and test a new, previously unconsidered explanation for the inverse relationship. We allow the productivity of plot j belonging to household i in time period t to be given by a combination of the productivity of the plot's interior, Y^I_{ijt}, and the productivity of the plot's periphery, Y^P_{ijt}, as suggested by the agronomy literature and shown in Equation 7. Productivity is weighted by the area of the plot's interior, A^I_{ijt} and the area of the plot's periphery, A^P_{ijt}, and the sum of these two areas gives the total area of the plot, A_{ijt}.

$$Y_{ijt} \equiv \frac{Y^I_{ijt} * A^I_{ijt} + Y^P_{ijt} * A^P_{ijt}}{A_{ijt}} \tag{7}$$

By re-arranging terms, Equation 7 can be re-written as in Equation 8.

$$Y_{ijt} \equiv \frac{Y^I_{ijt} * (A_{ijt} - A^P_{ijt}) + Y^P_{ijt} * A^P_{ijt}}{A_{ijt}} = Y^I_{ijt} + (Y^P_{ijt} - Y^I_{ijt}) * \frac{A^P_{ijt}}{A_{ijt}} \tag{8}$$

This last functional form suggests that plot productivity Y_{ijt} is an additive function of the productivity of the interior, Y^I_{ijt}, and the ratio of the plot's peripheral area A^P_{ijt} to

[14]The relative contribution of each variable within w_1 to X must be the same as the relative contribution of each variable within w_1 to Y. While unlikely to hold unless w_1 is a single variable, Oster (2016) notes that as long as deviations from this condition are not "extremely large," the calculated estimator will still provide an approximation of the consistent estimator.

[15]Under a second assumption of proportional selection — that X is equally related to w_1 and W_2 — β^* can be exactly calculated, using the same equation and letting $\delta = 1$. This approximation, however, allows a range of δ values to be considered.

the plot's total area A_{ijt}. However, while we view A_{ijt}, we do not view A^P_{ijt}, as we do not know the width of the peripheral area. Calculating A^P_{ijt}/A_{ijt} is therefore impossible.

We do, however, view the plot's GPS-measured perimeter, P_{ijt}. If we assume that A^P_{ijt} is roughly equivalent to $P_{ijt} * b$, where b is the width of the peripheral area, then we can can rewrite Equation 8 as in Equation 9.[16] Figure 1 provides a schematic visual for this assumption.

$$Y_{ijt} \approx Y^I_{ijt} + (Y^P_{ijt} - Y^I_{ijt}) * b * \frac{P_{ijt}}{A_{ijt}} \tag{9}$$

Equation 9 indicates that plot productivity should increase in P_{ijt}/A_{ijt}, given that b is a positive constant and we expect $(Y^P_{ijt} - Y^I_{ijt})$ to be positive. If this is the case, the inverse relationship could stem from mis-specification of the true data-generating process behind average plot productivity, since plot area A_{ijt} will necessarily be inversely correlated with P_{ijt}/A_{ijt}.

We can test this hypothesis by estimating Equation 10, in which γ_6 indicates the classic inverse relationship, and $\theta_1 = (Y^P_{ijt} - Y^I_{ijt}) * b$. If γ_6 becomes statistically insignificant and R^2 rises when we control for P_{ijt}/A_{ijt} in addition to A_{ijt}, then it would seem that the edge effect drives the inverse relationship.

$$Y_{ijt} = \gamma_6 A_{ijt} + \theta_1 \frac{P_{ijt}}{A_{ijt}} + \lambda_{ij} + \lambda_t + \varepsilon_{ijt} \tag{10}$$

While Equation 9 depends on the assumption that $A^P_{ijt} \approx P_{ijt} * b$ when b is small, for all plots of all shapes, this assumption can actually be quantified, and the result more rigorously shown for a variety of plot shapes. Appendix 7 contains such calculations for hypothetical circular, rectangular, and triangular plots. It additionally explores the possibility that b may not be small, relative to the total size of the plot. If b is not small, then we should find that plot productivity Y_{ijt} rises with P_{ijt}/A_{ijt} and also with A_{ijt}. This would be equivalent to finding that after controlling for P_{ijt}/A_{ijt} in Equation 10, the inverse size-productivity relationship reverses, such that $\hat{\gamma}_6 > 0$.

While Equation 10 will estimate $\hat{\theta}_1$ as an average treatment effect, we expect that the effect may truly be heterogeneous — both $(Y^P_{ijt} - Y^I_{ijt})$ and b may change with a variety of plot-specific features: adjacent plot characteristics, row organization, location on the landscape, etc. The estimated coefficient must therefore be viewed as a context-specific average treatment effect produced by heterogeneous biophysical and behavioral mechanisms, on which more below.

3.5 Edge Effect Mechanisms

Because we find that the edge effect entirely explains the inverse relationship, we next turn to investigating the mechanisms behind the edge effect. Two broad categories of mechanisms appear plausible. First, peripheral productivity Y^P_{ijt} may be higher than

[16]For intuition, we are basically assuming that the plot's periphery is thin enough to be rolled out from around the plot's perimeter in the form of a rectangle. Such a rectangle would not approximate the area of the plot's periphery if b was large with respect to the plot edges. But if b is small, e.g., one row of crops, then this rectangle approximates the peripheral area.

interior productivity Y^I_{ijt} due to higher levels of unobserved biophysical inputs such as sunlight, water, nutrients, drainage, pest protection or other agronomic factors generally unobservable to the econometrician but clearly important to plant growth. Because we do not view biophysical inputs we cannot test for such mechanisms directly. Appendix 8 reports a number of indirect tests, all inconclusive.

The second category of edge effect mechanisms involves farmer behavior rather than biophysical inputs. It may be that Y^P_{ijt} is higher than Y^I_{ijt} because farmers tend the more-visible edges of their plots differently than they tend plot interiors. Farmers might weed plot edges more carefully, space crops differently around plot edges, or harvest crops more assiduously around plot edges, where a missed plant will be visible when walking by.[17]

If this is the case, we might expect average labor per hectare L_{ijt} to exhibit the same pattern as average productivity per hectare. That is, we might expect a negative and significant $\hat{\gamma}_7$ if only A_{ijt} is included on the right hand side of Equation 11, but an insignificant $\hat{\gamma}_7$ estimate and a positive, significant $\hat{\theta}_2$ estimate if P_{ijt}/A_{ijt} is also controlled for, suggesting that spatial patterns in labor allocation could be a mechanism behind the edge effect.

$$L_{ijt} = \gamma_7 A_{ijt} + \theta_2 \frac{P_{ijt}}{A_{ijt}} + \lambda_{ij} + \varepsilon_{ijt} \tag{11}$$

If farmers invest more labor around the edges of their plots, this could reflect an increased awareness of the space around plot edges. To further investigate the productivity implications of "plot awareness" we examine a second and purely behavioral mechanism, one wholly unrelated to biophysical constraints or inputs. Recall that we have data on farmer-recalled plot size and also GPS-measured plot size. We calculate plot size perception error as the difference between these two sizes: $e_{ijt} \equiv A^F_{ijt} - A^{GPS}_{ijt}$, the magnitude of a farmer's over-estimation of her plot size. If farmers apply inputs based on perceived plot size, then input application rates and plot productivity should rise with perception error, signaling real resource allocation inefficiencies due to farmer cognitive and behavioral error.

In Equation 12, $\mathbb{1}(e_{ijt} > 0)$ is a binary variable indicating whether the size of plot j was over-estimated by farmer i in time period t, e^O_{ijt} gives positive perception errors as a percentage of plot size (i.e., $e^O_{ijt} = e_{ijt}/A_{ijt}$ for all $e_{ijt} > 0$), and e^U_{ijt} gives negative perception errors as a percentage of plot size (i.e., $e^U_{ijt} = e_{ijt}/A_{ijt}$ for all $e_{ijt} < 0$). Thus, κ^O and κ^U give the marginal effects of over- and underestimating plot size, respectively.

$$Y_{ijt} = \gamma_8 A_{ijt} + \theta_3 \frac{P_{ijt}}{A_{ijt}} + \kappa^B \mathbb{1}(e_{ijt} > 0) + \kappa^O e^O_{ijt} + \kappa^U e^U_{ijt} + \lambda_{ij} + \varepsilon_{ijt} \tag{12}$$

If, conditional on A_{ijt} and $\frac{P_{ijt}}{A_{ijt}}$, e_{ijt} is randomly distributed, then κ^O and κ^U capture the causal effect of farmer misperceptions on per hectare productivity. We test the conditional exogeneity of e_{ijt}, and then estimate $\hat{\kappa}^O$ and $\hat{\kappa}^U$.

[17] Farmers might also tend edges more intensively in order to signal plot ownership to neighbors, particularly if tenure status is questionable. We cannot investigate this mechanism due to a lack of variation in tenure status.

4 Results

4.1 Shadow Prices (Plot vs. Household Mechanisms)

Table 2 reports results for Equations 1-3. Panel 1 displays traditional, OLS estimates of the inverse relationship, as in Equation 1. Column 1 displays a significant, inverse relationship between farm size and plot productivity, while Column 2 displays a significant, inverse relationship between plot size and plot productivity. Explanatory power is greater in Column 2, however. When both farm size and plot size are controlled for in Column 3, the inverse relationship appears to exist only at the plot level.

In Panel 2, household-year-season fixed effects are introduced, as in Equation 2. That is, a fixed effect is included for every unique combination of household, year, and agricultural season.[18] This effectively controls for household- and time-specific shadow prices. Variation in plot size is identified only within households and within a season. (Estimating the association between farm size and productivity is therefore impossible.) The plot-level inverse relationship estimated in this panel is statistically significantly greater in magnitude than the comparable plot-level estimate in Panel 1. A 10 percent increase in plot size appears to drive a 5.7 percent decrease in plot productivity.[19]

In Panel 3, plot fixed effects are introduced, following Equation 3. Year and season are additional controls. This method therefore controls for plot-specific, time-invariant characteristics, reflecting plot-specific shadow prices or transaction costs related to distance to homestead or to road, location on the landscape, and time invariant soil characteristics. It also controls for any mean shifts in productivity or production technology across time. The plot-level inverse relationship estimates in Columns 2 and 3 of this panel are strong and statistically equivalent to the plot-level inverse relationship in Panel 2. As in Panel 1, farm size is superfluous once one controls for plot size. These results make it clear that the inverse relationship is a plot-level phenomenon, in these data at least, and not driven by inter-household heterogeneity in shadow prices or factor markets, as under the longstanding Chayanovian hypothesis.

For the remainder of this paper, main results are therefore estimated with plot fixed effects, controlling for year (2003 vs. 2013) and for season (1st vs. 2nd agricultural season) as dummies. The identifying variation is therefore within-plot, across-time variation in size, shape, and other plot characteristics. Plots that cannot be matched across the decade are necessarily dropped. Appendix 6 examines this selection process. Appendix 5 examines the non-random processes driving changes in plot size over time; essentially, larger plots are more likely to shrink, and smaller plots are more likely to grow. However, the inverse relationship exists for both shrinking and growing plots, as illustrated in Table A22 of Appendix 9. The same table shows the estimated inverse relationship remains unchanged if estimated using only those plots for which one 2003 plot was matched to one 2013 plot (rather than one 2003 plot matching to multiple 2013 plots or multiple 2003 plots to one 2013 plot). The relationship is also qualitatively unchanged across functional forms, as shown in Table A23.

[18]Most of Uganda has two agricultural seasons per year, so we define "time" from Section 3 as year-season.

[19]This relationship is similar across years, though the estimated coefficient is slightly larger in magnitude in 2013. See Table A19 in Appendix 9.

All results may instead be estimated with household-year-season fixed effects. Appendix 4 reports these results, where the identifying variation is across plots, within household-year-season groups. In this case, households with only one plot in any given year-season time period are dropped, a selection process again examined in Appendix 6. Explanatory power is lower when we exploit this dimension of variation. The coefficient estimates, however, are statistically (and qualitatively) the same as those estimated under plot fixed effects, with just two exceptions, both discussed in the appendix. We therefore confine discussion from here on to our preferred, plot fixed effects specification.

4.2 Measurement Error

Table 3 reports results for Equation 4, investigating whether measurement error around plot size drives or in fact mitigates the estimated inverse relationship. While the estimated relationship is statistically identical across measurement methods (GPS vs. farmer recall), the R^2 is considerably higher for the GPS-measured variables in Column 2 than for the farmer-recalled variables in Column 1. This is consistent with the results found by Carletto, Savastano and Zezza (2013), and counter to Lamb's (2003) hypothesis.[20]

As those authors noted, measurement error around plot size appears to weaken the relationship between plot size and productivity rather than strengthen it, at least in the Ugandan context. This is logical given that measurement error tends to be positive for smaller plots and negative for larger plots, both in our data and in the data examined by Carletto, Savastano and Zezza (2013). Figure 2 illustrates this relationship non-parametrically. The pattern makes smaller plots look less productive than they truly are, while large plots look more productive than they truly are.[21]

4.3 Omitted Variables and Causality

If plot size (or change in plot size over the decade) was randomly distributed, we could interpret the coefficient on GPS-measured plot size in Table 3 as the causal effect of plot size on plot productivity. This is not the case, however. Plot size is correlated with other, observable plot characteristics under any identification strategy — Table A24 in Appendix 9 illustrates this fact via regression-based balance tests under OLS, household-time fixed effects, and plot fixed effects.[22] In both the pooled and panel setting, therefore, plot size cannot be considered exogenous, and omitted variable bias is a threat to causal identification.

If omitted variables drive the inverse relationship, as suggested by Lamb (2003) or Assunção and Braido (2007), we would expect the coefficient estimate on plot size to diminish in absolute value as relevant, observable controls are introduced (Oster, 2016).

[20] Unlike the results by Carletto, Savastano and Zezza (2013), controlling for rounding in farmer-recalled plot size has no effect, and the coefficient estimate on a dummy for rounding is not significant.

[21] The bulk of plots fall within -3 and 1 on the x-axis of this figure.

[22] If 2003 plot size is included in the third column, almost all associations with other covariates become insignificant. That is, plot size change over the decade is primarily associated with other covariates through association with 2003 size. Nonetheless, as we do not control for 2003 plot size in our primary regressions, plot size change cannot be considered exogenous.

Table 4 introduces such controls, as specified in Equation 5, always controlling for plot fixed effects as well as year and season fixed effects. Column 1, beginning with no controls, is identical to Column 2 in Table 3 except for the loss of observations due to missing values of control variables needed in subsequent Columns.

Column 2 controls for soil characteristics. In Column 3, inputs such as labor hours, soil amendments and structures within the plot are added as controls.[23] The inverse relationship remains virtually identical in each of these specifications while the partial correlations between the controls and productivity are as one would expect. In Column 4 plot ownership and plot management is controlled for, and the inverse relationship becomes significantly larger in magnitude, as likewise occurs when crops are controlled for in Column 5. Column 6 controls for all variables simultaneously; the inverse relationship is statistically identical to the baseline estimate of Column 1.

While we control for management and crops by including them in Columns 4 and 5, one might wonder if instead the inverse relationship should be separately estimated across crop and management categories. Appendix 9 reports these results as a robustness check; the ratio does not change significantly across either category.

This stability of the estimated inverse relationship coefficient in Table 4 is remarkable, given the richness of these time-varying control variables and the fact that plot fixed effects control for all time-invariant, plot-level and household-level characteristics. However, it is possible that some other, still-omitted, time-varying plot characteristic drives the inverse relationship. The stability/robustness of the association is suggestive of but not proof of causality.

In order to explore the likelihood of causality we calculate Oster's bias-adjusted estimator γ^*, as defined in Equation 6. We do this allowing X_{ijt} from Equation 5 to be the full set of controls in Column 6 of Table 4,[24] and begin by assuming $\delta = 1$ and $R_{max} = 1.3R_5$, as suggested by Oster (2016). Under these assumptions, we obtain the extremely tight bounding interval [-0.667, -0.661]. Notably, these bounds suggest that the true, causal parameter is practically identical to the estimated parameter.

If we loosen these assumptions to allow a range of δ and R_{max} parameters, we again find that *all* possible bounds suggest that the causal inverse relationship is less than -0.6, i.e., very close to the estimated inverse relationship. Figure A6 in Appendix 10 illustrates these possible bounds. More details can be found in Appendix 10.

4.4 The Edge Effect

Having established the inverse relationship as strongly robust, very possibly causal, and unexplained by any previously considered mechanism, we now investigate the newly proposed edge effect mechanism. Columns 1-3 of Table 5 presents results for Equation 10, which specifies plot productivity as a function of the perimeter-area ratio, $\frac{P_{ijt}}{A_{ijt}}$. In Column 1, only plot size explains plot productivity, and the baseline inverse relationship is estimated. In Column 2 the perimeter-area ratio is additionally controlled for. This ratio is strongly, positively correlated with plot productivity, as we would expect if the

[23] Organic and inorganic fertilizer are controlled for in a binary fashion, as few plots receive either input.
[24] See Appendix 10 for bounds based on each set of controls in turn.

edges of a plot are more productive than the interior of a plot. Moreover, the inverse relationship is completely mitigated, becoming statistically identical to zero. Model R^2 also rises significantly in Column 2.

This result suggests that the inverse relationship is driven by a misspecification of the plot-level production function. In Column 3 plot size is dropped so that only the perimeter-area ratio is controlled for, and adjusted R^2 drops by only a percentage point, suggesting that plot size contributes very little additional information on average productivity once perimeter-area ratio is known.[25] In fact, adjusted R-squared is higher in Column 3 than in Column 1; perimeter-area ratio alone better explains plot productivity than does area alone.

Because $log(P_{ijt}/A_{ijt}) = log(P_{ijt}) - log(A_{ijt})$, we can alternatively specify the regression in Column 3 as in Column 4, controlling for perimeter and area separately. If Equation 10 specifies the true functional form, i.e., perimeter and area only predict productivity inso far as their ratio predicts productivity, then the same $\hat{\theta}_1$ coefficient will be estimated as the coefficient on each variable. Indeed, this is the case in Column 4.

Appendix 11 further explores evidence for the edge effect through a variety of robustness checks, placebo tests, and alternative specifications. The edge effect result is robust to all the controls of Table 4 (Table A27), can be estimated across crop and ownership/ management subsets (Tables A29-A30), and is virtually indistinguishable across both plot size quantiles and perimeter-area ratio quantiles (Table A31). Oster's bias-adjusted estimator γ^* again suggests that under reasonable assumptions, the edge effect is above zero (Table A28 and Figure A9). Table A32 illustrates that while plot shape does not directly drive productivity, it alters the marginal effect of perimeter-area ratio, which diminishes with the number of sides a plot has. For all shapes, however, the marginal edge effect is far above zero.

Because plot size and perimeter-area ratio are correlated (with a Pearson's correlation coefficient r=-0.133), and the log version of these variables is even more strongly correlated (r=-0.939), multicollinearity is a concern.[26] Yet the edge effect is indistinguishable across correlation quintiles (Table A33). Additionally, two placebo tests replace perimeter with a second variable, and while these new placebo-area ratios are highly correlated with area, just as perimeter-area ratio is, controlling for the placebo-area ratios does not mitigate the inverse relationship the way the true perimeter-area ratio does (Tables A34 and A35). These tests suggest that multicollinearity does not drive the results in Table 5.

Additionally, alternative proxies can be used to test for the edge effect, using number of sides (Table A36) or "extra/unecessary" perimeter (Table A37), rather than perimeter, to capture the peripheral area. As we would expect if these variables are an inferior proxy for peripheral area proportion, the estimated inverse relationship is attenuated but not wholly eliminated when controlling for number of sides or extra perimeter per hectare of plot.

[25]The fact that plot size contributes little or no information on productivity suggests, according to the theory outlined in Appendix 7, that the border area b defining plot edge is small.

[26]Though plot size and perimeter-area ratio are closely related, plot shape also explains a significant portion of perimeter-area ratio. See Table A26 in Appendix 11.

Implicit in our edge effect hypothesis is another: for plots where size and perimeter-area ratio move in the same direction over time, we should not observe an inverse relationship. Appendix 11 both simulates this effect and tests it empirically. Table A38 confirms that for plots where size and perimeter-area ratio both move in the same direction between 2003 and 2013, plot size is positively rather than negatively correlated with productivity.

These results strongly suggest the edge effect as an important explanation of the oft-observed size-productivity relationship. We note, however, that the magnitude of the estimated effect seems large. We explore the expected elasticity of productivity with respect to both plot size and perimeter-area ratio in the last section of Appendix 11. Using interior-peripheral differentials observed in agronomy literature, we simulate an edge effect that is almost half of the estimated coefficient on perimeter-area ratio. While we cannot be sure why the estimated effect is twice as high as the simulated effect, we do know that the interior-peripheral differentials discussed in agronomy literature usually stem from controlled agronomic trials, and therefore reflect biophysical mechanisms only. In farmer controlled plots, behavioral mechanisms may increase the differential between interior and peripheral productivity, increasing the edge effect. See Appendix 11 for more discussion.

While perimeter-area ratio completely mitigates the inverse relationship under plot fixed effects, Table A6 shows that under household-time fixed effects, the inverse relationship is only mitigated by about a third, more in line with theory-based expectations developed in Appendix 11. Because plot-specific shadow prices may bias estimation under household- time fixed effects, this remaining inverse relationship could be spurious correlation. However, it is also possible that while the edge effect explains much or all of the within-plot, over-time inverse relationship, other mechanisms drive the inverse relationship observed across plots within time periods. For example, Gourlay, Kilic and Lobell (2017) and Desiere and Jolliffe (2017) hypothesize that farmers over-estimate production on small plots and under-estimate it on large ones; if "small" and "large" are relative measures based on plot comparison, this mechanism might occur within time periods, but not across time within plots.

4.5 Edge Effect Mechanisms

We next explore mechanisms that might explain the edge effect. This section is necessarily more exploratory and suggestive in nature, as we cannot test for biophysical mechanisms directly. Appendix 8 reports indirect evidence regarding biophysical mechanisms. We find no evidence that sunlight or soil nutrient absorption drive the edge effect, though we cannot rule these mechanisms out. We do find that the edge effect is (insignificantly) larger in magnitude for mixed cropping and intercropped plots than for monocropped plots, as observed by Ward, Roe and Batte (2016).

Because we have labor input data, we can more directly examine evidence regarding a possible behavioral mechanism. Table 6 reports results for Equation 11, investigating whether the perimeter-area ratio drives labor intensity as well as plot productivity. In Column 1 labor intensity, measured in labor hours per hectare, is inversely correlated with plot size. In Column 2, however, it appears that the perimeter-area ratio drives much of the inverse relationship, as with productivity. Once the perimeter-area ratio is controlled for, the inverse relationship between plot size and labor intensity falls in absolute value by two-thirds, and is significant only at the 10 percent level. Additionally, controlling for perimeter-area ratio increases R^2 relative to Column 1, as in Table 5.

Column 3 controls only for perimeter-area ratio. Adjusted R^2 drops slightly relative to Column 2. This fact and the marginal significance on plot size in Column 2 suggest that plot size does contribute information on labor intensity, conditional on perimeter-area ratio, though not very much. The fact that the absolute value of the coefficient estimates on plot size and perimeter in Column 4 differ slightly also suggests that one of these variables may be associated with productivity outside of the association with their ratio. However, like the results from Table 5, the relative R^2 values of Columns 1 and 3 show that, if each variable is considered alone, perimeter-area ratio better captures the true data generating process than does plot size. This suggests (but cannot prove) that increased labor intensity around plot edges contributes to the edge effect, and hence helps to drive the inverse relationship.[27,28] Appendix 8 reports additional results for family and non-family laborers and across various types of labor; differences in effect are not large or particularly meaningful.

Last, we examine how farmer perception errors concerning plot area impact plot productivity. If perception error is exogenous to other plot conditions, then any labor or productivity response to perception error can be viewed as a purely behavioral mechanism. Appendix 12 investigates this exogeneity. While perception error is clearly related to plot size and the perimeter-area ratio when all data are pooled, under a plot fixed effects model it appears largely unrelated to plot conditions. If conditioned on plot area and perimeter-area ratio, perception error appears exogenous to all other time varying, plot-level characteristics, with the potential exception of crop cultivated, which is in any case a farmer behavioral choice.

Table 7 demonstrates the effect of farmer misperceptions of plot size on productivity. Plot productivity rises with over-estimation (at a diminishing rate), and drops with under-estimation (also at diminishing rate).[29] Column 1 controls for log plot area and log plot perimeter-area ratio in addition to farmer perceptions, and Column 2 controls for area and perimeter-area ratio quadratically.[30] Column 3 controls for area and perimeter-area ratio quadratically and additionally controls for all typically “omitted” variables from Column 6 of Table 4. The effect of farmer perceptions remains qualitatively and statistically the same across all specifications.

[27]Additionally, the edge effect seems to affect labor intensity and productivity in the same way: the third columns of Table 5 and Table 6 suggest a roughly one-to-one increase in both productivity and labor intensity. As discussed in Appendix 11, this elasticity is higher than expected, and could be driven by a few factors. Visible edges may increase application of labor farther into the plot than the peripheral area that enjoys a biophysical edge effect. Shape may also be endogenously chosen to maximize ease of labor, in a way not fully understand.

[28]It is important to note here that this relationship implies that labor is being applied at higher rates around plot edges, not that labor is more effective around plot edge, a possibility we cannot gauge in these data.

[29]Note that over-estimation is, on average, much larger in magnitude than under-estimation, which is bounded from below by zero. The productivity impacts of over-estimation are therefore much greater than the productivity impacts of under-estimation.

[30]Appendix 12 suggests that perceptions may respond non-linearly to area and perimeter-area ratio.

The results in Table 7 suggest that farmers' misperceptions of plot size impact plot productivity. This presumably occurs through behavioral channels only, since misperceptions seem to be exogenous to plot characteristics, conditional on plot size and perimeter-area ratio. If farmers apply more (less) inputs and labor to larger (smaller) plots, as they clearly do, it seems logical that an over- (under-) estimate of plot size would lead to inefficient allocation of resources, and higher (lower) productivity. In fact, Table A44 in Appendix 13 shows that labor intensity does respond in this way to farmer over-estimation of plot size, though the results are not as strong as they are for productivity.[31]

Because Appendix 12 suggest that perception error may possibly be related to crop type, Appendix 13 presents the same regressions by crop, as well as by ownership/ management category. The results are qualitatively similar to those of Table 7, though not always significant since sample size falls drastically.

It is also possible that misperceptions of plot size impact not plot productivity itself but rather *perceived* plot productivity. A farmer who believes his/her plot to be larger than it is may be more likely to over-report yields, while a farmer who under-estimates size may under-report yields. With these data we cannot differentiate such a phenomenon from the behavioral phenomenon wherein farmers actually allocated inputs according to their perceptions of plot size, and truly experience higher or lower yields as a result.

5 Conclusion

Using plot-level panel data for the first time in this literature, we estimate the inverse size-productivity relationship under plot fixed effects. We show that the inverse relationship exists at the plot level and thus cannot be explained by household shadow prices or by other, omitted household characteristics. Additionally, the inverse relationship estimated under plot fixed effects is statistically identical to that estimated under household-time fixed effects. This stability across two identification methods, each exploiting different variation in the data and vulnerable to different sources of potential bias, suggests that the relationship may be causal. We estimate bounds around the likely causal relationship between plot size and plot productivity, using the consistent estimator of bias derived by Oster (2016). This exercise suggests that the causal relationship is significant and large in magnitude; a 10 percent increase in plot size decreases plot productivity by 6.1-6.7 percent.

We also validate the findings of Carletto, Savastano and Zezza (2013), Barrett, Bellemare and Hou (2010) and Carletto, Gourlay and Winters (2015) by showing that neither soil fertility nor measurement error around plot size drives a spurious, inverse relationship between plot size and plot productivity. By controlling for a rich set of plot characteristics such as lab-measured soil fertility, inputs and management practices, we show that the inverse relationship cannot be explained by the time-varying plot characteristics typically considered.

[31] This makes sense. If farmers choose input intensity based on plot size perceptions, we would expect a stronger relationship between resulting productivity and perceptions than between any individual input and perceptions.

While previously proposed mechanisms do not explain the inverse relationship, our analysis suggests that it might be explained by edge effects familiar in the agronomy literature. We show that plot productivity rises with perimeter-area ratio, and under plot fixed effects, plot area has no remaining influence on productivity once perimeter-area ratio is controlled for.[32] This does not prove that the edge effect drives the inverse relationship. However, this pattern is exactly what we expect to find if plot peripheries/edges are more productive than plot interiors, and if the width of this peripheral area is narrow. Therefore, in these data at least, particularly when it comes to variation in plot size and productivity over time, it seems likely that the inverse relationship is at least partially driven by the more productive peripheral area around the edge of each plot, which necessarily makes smaller plots more productive on average than large plots.

The mechanism behind the edge effect is difficult to isolate; in all likelihood there are multiple mechanisms. The agronomy literature suggests that the periphery of a plot is often more productive than the interior of a plot due to increased inputs such as sunlight exposure, access to water or nutrient uptake (Watson and French, 1971; O'Brien and Green, 1974; Barchia and Cooper, 1996; Balagawi, Jackson and Clarke, 2014). We do not observe these inputs directly, but find no indirect evidence of such biophysical mechanisms.

The mechanism behind the edge effect is difficult to isolate; in all likelihood there are multiple mechanisms, some biophysical and others perhaps behavioral. The agronomy literature suggests that the periphery of a plot is often more productive than the interior of a plot due to increased inputs such as sunlight exposure, access to water or nutrient uptake(Watson and French, 1971; O'Brien and Green, 1974; Barchia and Cooper, 1996; Balagawi, Jackson and Clarke, 2014). We do not observe these inputs directly, but find no indirect evidence of such biophysical mechanisms.

We do, however, observe that plot-level labor intensity rises with perimeter-area ratio, just as productivity does. This suggests a behavioral mechanism — if farmers are more aware of plot edges, and/or can more easily access plot edges, they may tend these edges more intensely in weeding, pruning, or even harvesting. This could contribute to the edge effect, and to the inverse relationship. The behavioral economics literature shows that consumer behavior responds strongly to visual cues (Wansink, Painter and North, 2005). Our results suggest that perhaps production does the same.

We additionally show that farmer beliefs about plot size — independent of actual plot size — may influence investments in plots and therefore plot productivity, just as portion labeling influences consumer reference frames for portion size, and therefore influences food consumption choices (Just and Wansink, 2014). Farmer misperceptions of plot size, which we show are exogenous to other plot characteristics conditional on plot size and perimeter-area ratio, are strongly associated with plot productivity. Marginal increases in plot size over-estimation (under-estimation) are positively (negatively) and significantly associated with plot productivity. These results suggest that farmer cognitive error may influence input application rates and thus productivity, consistent with the possibility of an edge effect driven by labor allocation behaviors.

[32]The perimeter-area ratio is similarly positively associated with productivity under household-time fixed effects, but the inverse relationship is not fully mitigated.

Taken together, our results suggest not only that the inverse relationship is at the plot, rather than farm level, but also that both plot size and plot *shape* drive productivity. Robustness checks suggest that a number of plot shape characteristics influence productivity, all in line with the edge effect. The fact that labor intensity as well as productivity rises with increased peripheral area further suggests that the edge effect drives the inverse relationship, and that a behavioral mechanism may be at play. Further research might tease out both the mechanisms behind and the heterogeneity within the edge effect. Plots bordering large trees, for instance, might benefit less from the edge effect; the direction of crops rows might also influence the magnitude of the edge effect. Such knowledge could influence optimal layout and organization of plots. This paper shows, however, that the inverse relationship is a plot-level phenomenon, and that farmer choices regarding plot shape as well as plot size influence productivity.

References

Akram-Lodhi, Haroon. 2001. “Vietnam’s agriculture: is there an inverse relationship?” *ISS Working Paper Series/General Series*, 348: 1–36.

Ali, Daniel Ayalew, and Klaus Deininger. 2015. “Is there a farm size–productivity relationship in African agriculture? Evidence from Rwanda.” *Land Economics*, 91(2): 317–343.

Altonji, Joseph G, Todd E Elder, and Christopher R Taber. 2005. “Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools.” *Journal of Political Economy*, 113(1): 151–184.

Alvarez, Antonio, and Carlos Arias. 2004. “Technical efficiency and farm size: a conditional analysis.” *Agricultural Economics*, 30(3): 241–250.

Assunção, Juliano J, and Luis HB Braido. 2007. “Testing household-specific explanations for the inverse productivity relationship.” *American Journal of Agricultural Economics*, 89(4): 980–990.

Balagawi, Solomon, Kevin Jackson, and AR Clarke. 2014. “Resting sites, edge effects and dispersion of a polyphagous Bactrocera fruit fly within crops of different architecture.” *Journal of Applied Entomology*, 138(7): 510–518.

Barchia, I, and JL Cooper. 1996. “Edge row effects on yields in an oat trial.” *Animal Production Science*, 36(4): 459–461.

Bardhan, Pranab K. 1973. “Size, productivity, and returns to scale: An analysis of farm-level data in Indian agriculture.” *The Journal of Political Economy*, 1370–1386.

Barrett, Christopher B. 1996. “On price risk and the inverse farm size-productivity relationship.” *Journal of Development Economics*, 51(2): 193–215.

Barrett, Christopher B, Marc F Bellemare, and Janet Y Hou. 2010. “Reconsidering conventional explanations of the inverse productivity–size relationship.” *World Development*, 38(1): 88–97.

Benjamin, Dwayne. 1995. “Can unobserved land quality explain the inverse productivity relationship?” *Journal of Development Economics*, 46(1): 51–84.

Benjamin, Dwayne, and Loren Brandt. 2002. “Property rights, labour markets, and efficiency in a transition economy: the case of rural China.” *Canadian Journal of Economics*, 689–716.

Berry, R Albert, and William R Cline. 1979. *Agrarian structure and productivity in developing countries: a study prepared for the international labour pffice within the framework of the World Employment Programme.* Johns Hopkins University Press.

Bhalla, Surjit S, and Prannoy Roy. 1988. “Mis-specification in farm productivity analysis: the role of land quality.” *Oxford Economic Papers*, 55–73.

Carletto, Calogero, Sara Savastano, and Alberto Zezza. 2013. “Fact or artifact: the impact of measurement errors on the farm size–productivity relationship.” *Journal of Development Economics*, 103: 254–261.

Carletto, Calogero, Sydney Gourlay, and Paul Winters. 2015. "From guesstimates to GPStimates: Land area measurement and implications for agricultural analysis." *Journal of African Economies*, 24(5): 593–628.

Carletto, Calogero, Sydney Gourlay, Siobhan Murray, and Alberto Zezza. 2016. "Cheaper, faster, and more than good enough: is GPS the new gold standard in land area measurement?" World Bank Policy Research Working Paper 7759.

Carter, Michael R. 1984. "Identification of the inverse relationship between farm size and productivity: an empirical analysis of peasant agricultural production." *Oxford Economic Papers*, 131–145.

Carter, Michael R, and Yang Yao. 2002. "Local versus global separability in agricultural household models: The factor price equalization effect of land transfer rights." *American Journal of Agricultural Economics*, 84(3): 702–715.

Chayanov, Alexander. 1991. *The theory of peasant co-operatives.* IB Tauris.

Collier, Paul. 1983. "Malfunctioning of African rural factor markets: Theory and a Kenyan example." *Oxford Bulletin of Economics and Statistics*, 45(2): 141–172.

Desiere, Sam, and Dean Jolliffe. 2017. "Land productivity and plot size: Is measurement error driving the inverse relationship?" Paper Presented at the 2017 Centre for the Study of African Economies (CSAE) Conference.

Feder, Gershon. 1985. "The relation between farm size and farm productivity: The role of family labor, supervision and credit constraints." *Journal of Development Economics*, 18(2): 297–313.

Gourlay, Sydney, Talip Kilic, and David Lobell. 2017. "Could the debate be over? Errors in farmer-reported production and their implications for inverse scale-productivity relationship in Uganda." Paper Presented at the 2017 Centre for the Study of African Economies (CSAE) Conference.

Heltberg, Rasmus. 1998. "Rural market imperfections and the farm size—productivity relationship: Evidence from Pakistan." *World Development*, 26(10): 1807–1826.

Henderson, Heath. 2015. "Considering Technical and Allocative Efficiency in the Inverse Farm Size–Productivity Relationship." *Journal of Agricultural Economics*, 66(2): 442–469.

Holman, E Merritt, and Craig W Bednarz. 2001. "Alley effect on several cotton cultivars in small plot research." *Communications in Soil Science and Plant Analysis*, 32(1-2): 119–126.

Just, David R, and Brian Wansink. 2014. "One man's tall is another man's small: How the framing of portion size influences food choice." *Health Economics*, 23(7): 776–791.

Kagin, Justin, J Edward Taylor, and Antonio Yúnez-Naude. 2015. "Inverse Productivity or Inverse Efficiency? Evidence from Mexico." *The Journal of Development Studies*, 1–16.

Kimhi, A. 2006. "Plot size and maize productivity in Zambia: The inverse relationship re-examined." *Agricultural Economics*, 35: 1–9.

Krauth, Brian. 2016. "Bounding a linear causal effect using relative correlation restrictions." *Journal of Econometric Methods*, 5(1): 117–141.

Lamb, Russell L. 2003. "Inverse productivity: Land quality, labor markets, and measurement error." *Journal of Development Economics*, 71(1): 71–95.

Larson, Donald F, Keijiro Otsuka, Tomoya Matsumoto, and Talip Kilic. 2014. "Should African rural development strategies depend on smallholder farms? An exploration of the inverse-productivity hypothesis." *Agricultural Economics*, 45(3): 355–367.

Little, Thomas M, and Frederick Jackson Hills. 1978. *Agricultural Experimentation: Design and Analysis.* John Wiley and Sons. New York, NY, USA.

Mazumdar, Dipak. 1965. "Size of farm and productivity: a problem of Indian peasant agriculture." *Economica*, 32(126): 161–173.

Nkonya, Ephraim, John Pender, Kayuki C Kaizzi, Edward Kato, Samuel Mugarura, Henry Ssali, and James Muwonge. 2008. *Linkages between land management, land degradation, and poverty in Sub-Saharan Africa: The case of Uganda.* Vol. 159, International Food Policy Research Institute.

O'Brien, L, and RT Green. 1974. "Plot width and cultivar interaction." *Journal of the Australian Institute of Agricultural Science*, 40: 158–159.

Oster, Emily. 2016. "Unobservable selection and coefficient stability: theory and evidence." *Journal of Business Economics and Statistics*, DOI: 10.1080/07350015.2016.1227711.

Rios, Ana R, and Gerald E Shively. 2005. "Farm size and nonparametric efficiency measurements for coffee farms in Vietnam." In *Technical Report 19159, 2005 Annual Meeting.* American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association).

Sen, Amartya K. 1962. "An aspect of Indian agriculture." *Economic Weekly*, 14(4-6): 243–246.

Sen, Amartya K. 1966. "Peasants and Dualism with or without Surplus Labor." *Journal of Political Economy*, 74(5): 425–450.

Tittonell, PABLO, Bernard Vanlauwe, N De Ridder, and Ken E Giller. 2007. "Heterogeneity of crop productivity and resource use efficiency within smallholder Kenyan farms: Soil fertility gradients or management intensity gradients?" *Agricultural Systems*, 94(2): 376–390.

Tittonell, P, Bernard Vanlauwe, PA Leffelaar, Keith D Shepherd, and Ken E Giller. 2005. "Exploring diversity in soil fertility management of smallholder farms in western Kenya: II. Within-farm variability in resource allocation, nutrient flows and soil fertility status." *Agriculture, Ecosystems & Environment*, 110(3): 166–184.

Van Zyl, Johan, Hans Binswanger, and Colin Thirtle. 1995. "The relationship between farm size and efficiency in South African agriculture." World Bank.

Verdelli, Diego, Horacio A Acciaresi, and Eduardo S Leguizamón. 2012. "Corn and soybeans in a strip intercropping system: crop growth rates, Radiation interception, and grain yield components." *International Journal of Agronomy*, 2012.

Wansink, Brian, James E Painter, and Jill North. 2005. "Bottomless Bowls: Why Visual Cues of Portion Size May Influence Intake." *Obesity Research*, 13(1): 93–100.

Ward, Barry, Brian E Roe, and Marvin T Batte. 2016. "Potential Profitability of Strip Intercropping with Corn and Soybeans." *Journal of the ASFMRA*.

Watson, DJ, and SAW French. 1971. "Interference between rows and between plants within rows of a wheat crop, and its effects on growth and yield of differently-spaced rows." *Journal of Applied Ecology*, 421–445.

Figures

Figure 1: Plot Area Schematic

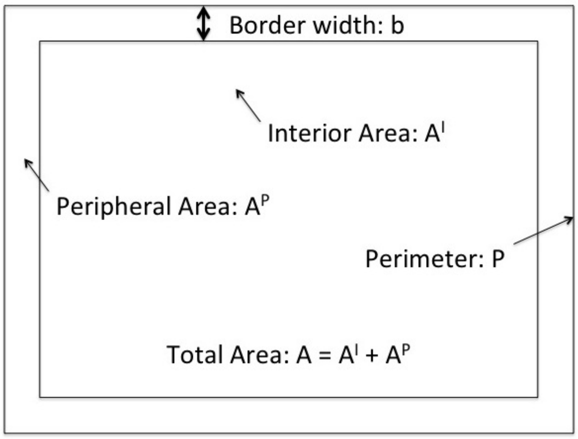
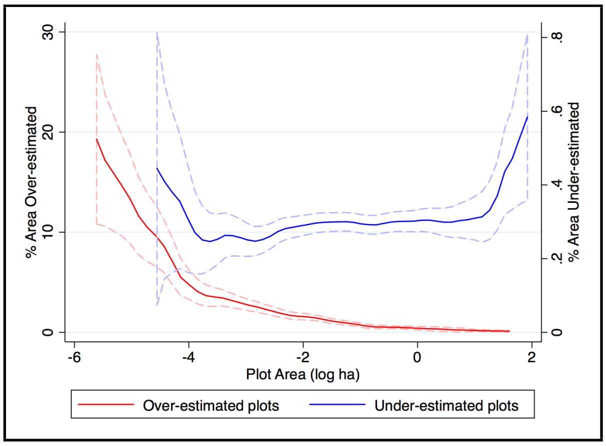


Figure 2: Misperceptions by Plot Area



Tables

Table 1: Plot Characteristics in 2003 and 2013

	2003		2013		
	Mean or Median†	Standard Deviation	Mean or Median†	Standard Deviation	T Statistic‡
Size, Productivity, Labor					
Farm size (ha)	1.04	1.19	0.57	0.88	15.83***
Plot size (ha)	0.35	0.68	0.18	0.40	12.21***
Perimeter-area ratio (m/ha)	849.45	925.11	1,146.56	6,778.42	-10.08***
Plot productivity (revenue§/ha)	103.06	1,328.82	256.12	8,653.08	-18.06***
Labor intensity (hrs/ha/day)	1.94	9.61	1.78	67.70	1.49
Soils					
Soil pH (pH)	6.23	0.52	6.18	0.63	1.96*
Soil sand (%)	60.12	14.05	52.65	15.82	10.82***
Soil organic carbon (%)	3.45	1.65	3.72	1.87	-3.27***
Inputs					
Organic amendment (%)	19.89	39.94	12.01	32.52	5.06***
Inorganic fertilizer (%)	1.19	10.86	1.47	12.03	-0.56
Irrigation (%)	1.30	11.33	0.19	4.32	3.01***
Terracing (%)	23.19	42.22	9.37	29.15	8.89***
Management					
Head manages plot (%)	55.36	49.73	63.70	48.11	-3.98***
(Head owns)X(Head manages)	46.47	49.90	59.30	49.15	-6.05***
Crops are rotated (%)	21.75	41.27	42.87	49.52	-10.26***
Crops are mono-cropped (%)	42.99	49.53	36.94	48.29	2.89***
Mixed cropping (%)	54.54	49.82	52.06	49.98	1.16
Intercropping (%)	2.47	15.54	10.91	31.19	-7.99***
Crops Grown					
Tubers grown (%)	43.35	49.58	24.84	43.23	9.30***
Cereals grown (%)	49.50	50.02	43.63	49.62	2.75***
Legumes grown (%)	53.07	49.93	45.10	49.78	3.74***
Bananas grown (%)	48.67	50.01	27.59	44.72	10.38***
Cash crops grown (%)	30.98	46.26	18.97	39.23	6.54***

†The first 5 variables are all distributed log-normally, and therefore median is listed and T-statistics are generated using the log variable. For all other variables mean is listed and T-statistics are generated using the variable directly.

‡ *** p<0.01, ** p<0.05, * p<0.1

§ Revenue is given in real, 2005-valued dollars.

Table 2: Household Shadow Prices and the Inverse Relationship (Plots Pooled)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity
	Panel 1 (No FE)		
Farm size (log ha)	-0.378***		-0.0358*
	(0.0188)		(0.0217)
Plot size (log ha)		-0.516***	-0.496***
		(0.0159)	(0.0198)
Observations	5709	5709	5709
Adjusted R^2	0.073	0.171	0.172
	Panel 2 (House-year-season FE)		
Plot size (log ha)		-0.565***	
		(0.0259)	
Observations		4845	
Adjusted R^2		0.170	
	Panel 3 (Plot FE)		
Farm size (log ha)	-0.321***		0.0634
	(0.0875)		(0.0618)
Plot size (log ha)		-0.621***	-0.648***
		(0.0636)	(0.0637)
Observations	2181	2181	2181
Adjusted R^2	0.282	0.381	0.381

Dependent variable: log(revenue/hectare)
Panel 1 (Eq 1): No FE, robust standard errors
Panel 2 (Eq 2): HH-yr-ssn FE, HH-yr-ssn clustered standard errors
Panel 3 (Eq 3): Plot FE, yr and ssn FE, plot clustered standard errors
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Measurement Error and the Inverse Relationship (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity
Farmer-recalled plot size (log ha)	-0.629***	
	(0.0496)	
GPS-measured plot size (log ha)		-0.621***
		(0.0636)
Observations	2175	2181
Adjusted R^2	0.229	0.381

Col 1 dependent variable: log(revenue/farmer-recalled-hectare)
Col 2 dependent variable: log(revenue/GPS-measured-hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 4
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Omitted Variables and the Inverse Relationship (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity	(4) Plot Productivity	(5) Plot Productivity	(6) Plot Productivity
GPS-measured plot size (log ha)	-0.670***	-0.662***	-0.603***	-0.712***	-0.728***	-0.667***
	(0.0965)	(0.0994)	(0.0900)	(0.0925)	(0.0921)	(0.0864)
Soil pH (pH)		2.239*				0.711
		(1.306)				(1.351)
Soil pH^2 (pH^2)		-0.159				-0.0329
		(0.107)				(0.112)
Soil sand (%)		-0.00374				-0.00468
		(0.00593)				(0.00560)
Soil organic carbon (%)		-0.00942				-0.0218
		(0.0403)				(0.0447)
Labor intensity (log hrs/ha/day)			0.106**			0.102**
			(0.0425)			(0.0416)
Organic amendment (binary)			0.0497			0.0750
			(0.148)			(0.156)
Inorganic fertilizer (binary)			1.559***			1.299***
			(0.204)			(0.315)
Irrigation (binary)			0.0637			-0.283
			(0.372)			(0.432)
Terracing (binary)			0.423***			0.465***
			(0.137)			(0.145)
Head owns plot (binary)				-0.111		-0.104
				(0.164)		(0.160)
Head manages plot (binary)				0.268		0.119
				(0.207)		(0.206)
(Head owns)X(Head manages)				-0.0558		0.000317
				(0.241)		(0.236)
Crops are rotated (%)				-0.0969		0.0434
				(0.118)		(0.116)
Crops are mono-cropped (%)				0.0776		0.0557
				(0.263)		(0.264)
Mixed cropping (%)				0.507*		0.414
				(0.266)		(0.262)
Tubers grown (binary)					0.101	0.00536
					(0.117)	(0.114)
Cereals grown (binary)					0.0836	-0.00553
					(0.109)	(0.105)
Legumes grown (binary)					0.202**	0.0617
					(0.102)	(0.113)
Bananas grown (binary)					0.148	0.117
					(0.168)	(0.163)
Cash crops grown (binary)					0.676***	0.522***
					(0.177)	(0.173)
Observations	1623	1623	1623	1623	1623	1623
Adjusted R^2	0.370	0.378	0.390	0.390	0.390	0.425
R^2	0.371	0.380	0.393	0.393	0.393	0.433

Dependent variable: log(revenue/hectare)
All columns estimated using only the sample for Column 6
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 5
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Edge Effect and the Inverse Relationship (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity	(4) Plot Productivity
GPS-measured plot size (log ha)	-0.621***	-0.124		-1.027***
	(0.0636)	(0.126)		(0.128)
Perimeter-area ratio (log m/ha)		0.903***	1.099***	
		(0.231)	(0.0961)	
Perimeter (log m)				0.903***
				(0.231)
Observations	2181	2181	2181	2181
Adjusted R^2	0.381	0.393	0.392	0.393

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 10
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Edge Effect and Labor Intensity (Plot Panel)

	(1) Labor Intensity	(2) Labor Intensity	(3) Labor Intensity	(4) Labor Intensity
GPS-measured plot size (log ha)	-0.682***	-0.264*		-1.019***
	(0.0626)	(0.141)		(0.126)
Perimeter-area ratio (log m/ha)		0.755***	1.169***	
		(0.242)	(0.0939)	
Perimeter (log m)				0.755***
				(0.242)
Observations	2076	2076	2076	2076
Adjusted R^2	0.186	0.196	0.193	0.196

Dependent variable: log(hours/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 11
*** p<0.01, ** p<0.05, * p<0.1

Table 7: The Effects of Farmer Misperception of Plot Size (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity
Farmer over-estimates plot (binary)	-0.405***	-0.400***	-0.329*
	(0.136)	(0.136)	(0.177)
Over-estimate (% area)	0.157***	0.154***	0.110***
	(0.0337)	(0.0332)	(0.0404)
Over-estimate squared	-0.00378***	-0.00444***	-0.00343**
	(0.00135)	(0.00124)	(0.00151)
Under-estimate (% area)	-2.242***	-2.156***	-2.726**
	(0.767)	(0.761)	(1.147)
Under-estimate squared	2.718***	2.464***	3.324**
	(0.917)	(0.904)	(1.455)
Plot Area, P-A Ratio	Yes	Yes	Yes
$(\text{Area})^2$, $(\text{P-A Ratio})^2$	No	Yes	Yes
Additional Plot Controls	No	No	Yes
Observations	2181	2181	1623
Adjusted R^2	0.414	0.424	0.455

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Additional plot controls are from Column 6 of Table 3
Table estimates Equation 12
*** p<0.01, ** p<0.05, * p<0.1

Appendix 1 More on GPS: Plot Size, Perimeter, Geospatial Matching

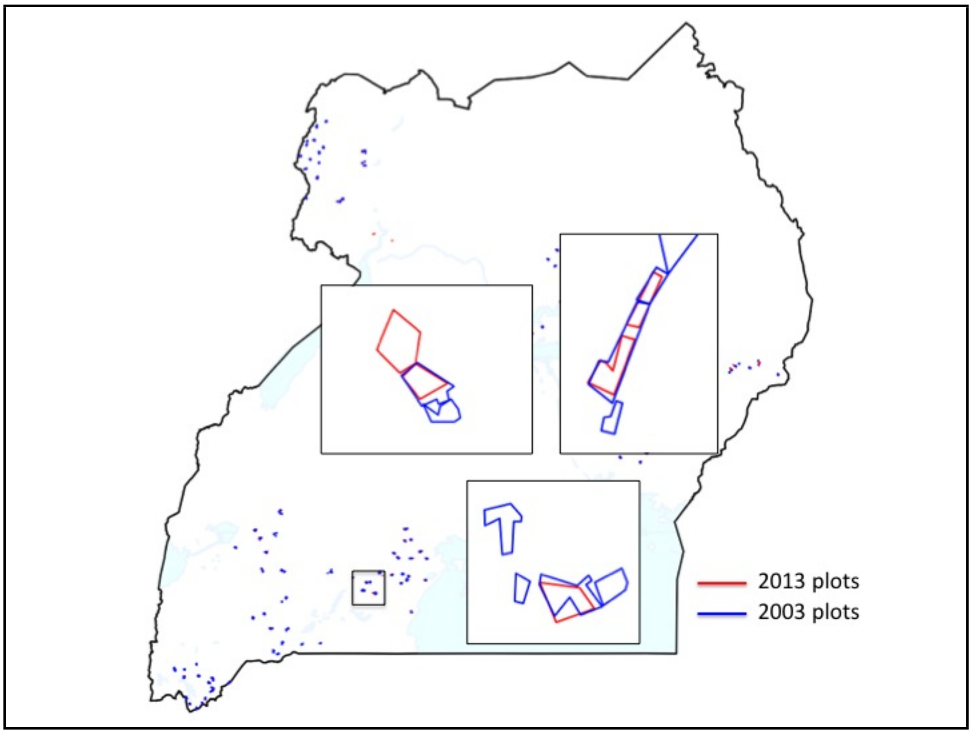
In both 2003 and 2013, enumerators collected GPS waypoints around the perimeter of each plot. In 2003 they did this by slowly walking around the plot while the GPS unit took waypoints at automated intervals, pausing at corners and flex-points in order to capture vertices. In 2013 they did this more explicitly by walking to each corner or flex-point of a plot and taking a single waypoint there. In each year they additionally took waypoints at what appeared to be the center of the plot.

The perimeter of each plot was then created via GIS by connecting the waypoints taken around each plot. (Because in most cases plots are fairly standard sizes, generally rectangles or triangles, these perimeters are fairly accurate.) Plot size was calculated as the precise area within each perimeter. (Altitude/slope was not used, as accurate measures were not available, and additionally plots are generally too small for this to be necessary.) New plot centroids were also generated based on the GIS-determined perimeter.

While GPS measurement is not without error, Carletto et al. (2016) illustrate that this error is not a source of concern when recording plot sizes. While it seems possible that the 2003 method of recording waypoints was more subject to error, we have no way of testing this hypothesis. However, measurement error will manufacture an inverse relationship, as plots that were under-estimated in size (appearing smaller) will be over-estimated in terms of revenue per hectare, while plots that were over-estimated in size (appearing larger) will be under-estimated in terms of revenue per hectare. If measurement error was greater in 2003 than in 2013, we might expect to see a stronger inverse relationship in round 1. In fact, the opposite is observed. We have no reason to suspect, therefore, that measurement error in either round is driving any part of our results.

To match plots geospatially over time, plot shapefiles were overlaid upon one another in ArcGIS as shown by Figure A1. It was more often found that a 2003 plot geospatially overlapped with multiple 2013 plots (as in the example at the top right of A1) than the reverse, due to the general trend of plots becoming smaller over the decade. Thus, we maintain 2013 plots as the unique observation, and match each 2013 plot to one 2003 plot. In 70 percent of cases, the 2013 plot overlaps only one 2003 plot. The rest of 2013 plots overlap multiple 2003 plots — in these cases the 2003 plot of greatest area overlap is matched. In some cases multiple 2013 plots end up matched to the same 2003 plot. In fact, 26 percent of 2013 plots are matched to a 2003 plot that is also matched to a different 2013 plot — the top right zoom in of A1 shows an example of three 2013 plots that each end up matched to the same 2003 plots.

Figure A1: Overlaying 2003 and 2013 plot shapefiles



Appendix 2 Survey Attrition

Of the 849 households interviewed in 2003, 728 households (86 percent of the original sample) was tracked for re-interview. Households were reinterviewed if they were living in the same location, or tracked to a new location and re-interviewed if they were living in the same parish. Households who had moved out of the parish were not tracked. Additionally, 10 communities were not visited in 2013 — 1 in northern Uganda, and 9 in the south-west. Fifty-eight percent of attritted households come from these 10 communities, and 42 percent are distributed across the other communities.

Table A1 examines differences between the 2003 characteristics of tracked and attritted households. Households that attritted were significantly more educated, a bit younger, and a bit smaller than tracked households. Households that attritted were also slightly further from markets, had larger plots and farms, and had better soil quality.

These differences conflate the two types of attrition, however. Table A2 differentiates between households that attritted by community and households that attritted individually. Households that attritted by community tend to be further from markets and roads, make more money in crop income, and have better soil quality than tracked households. These statistics reflect the fact that more remote communities, which were difficult and expensive to travel to, were more likely to be dropped from the 2013 survey. Households that attritted individually (i.e., had simply moved out of a community that was included in the 2013 survey) had smaller farms and made less money that tracked households, but were also younger and more educated. This likely reflects a combination of individual push and pull factors driving migration out of the local parish.

Table A1: Household-level Attrition From 2003 to 2013

	Tracked		Attritted		
	Mean	St Dev	Mean	St Dev	T-stat
Head years of education (#)	4.88	3.36	5.56	3.13	-2.08**
Head age (#)	41.97	14.08	37.96	12.97	2.92***
Household size (# people)	5.97	2.81	5.15	2.88	2.92***
Asset index (index)	13.99	0.93	14.06	0.82	-0.70
Net crop income (1,000 Ush)	494.12	1,259.58	708.30	1,750.85	-1.43
Distance to all weather road (km)	2.57	4.64	2.52	2.72	-1.65*
Distance to market (km)	3.04	3.52	3.58	3.07	-1.83*
Farm size (ha)	1.41	2.52	1.65	6.45	2.02**
Number of plots owned (#)	4.56	2.20	5.30	3.16	-2.45**
Average plot area (ha)	0.63	1.19	1.08	6.24	2.05**
Crops provide primary income (%)	68.87	46.33	45.45	50.00	5.09***
Number of cattle (#)	2.36	6.24	1.88	7.20	0.71
Soil pH (pH)	6.16	0.47	6.13	0.58	0.63
Soil carbon (%)	3.16	1.51	4.15	1.85	-6.02***
Soil sand (%)	62.92	13.78	57.38	12.64	3.87***

Table A2: Household-level Attrition: Community vs. HH-level Attrittition

	Tracked		Attritted by Comm			Attritted by HH		
	Mean	St Dev	Mean	St Dev	T-stat	Mean	St Dev	T-stat
Head years of education (#)	4.88	3.36	5.33	3.14	-1.07	5.88	3.11	-2.07**
Head age (#)	41.97	14.08	39.23	14.05	1.54	36.24	11.24	2.85***
Household size (# people)	5.97	2.81	5.10	2.80	2.47**	5.21	3.03	1.78*
Asset index (index)	13.99	0.93	14.16	0.76	-1.36	13.89	0.90	0.60
Net crop income (1,000 Ush)	494.12	1,259.58	1,104.59	2,006.55	-4.02***	164.37	1,131.06	2.50**
Distance to all weather road (km)	2.57	4.64	3.45	3.04	-3.99***	1.23	1.45	2.11**
Distance to market (km)	3.04	3.52	4.50	3.24	-3.71***	2.30	2.28	1.47
Farm size (ha)	1.41	2.52	2.06	8.23	0.30	1.09	2.41	2.92***
Number of plots owned (#)	4.56	2.20	6.10	3.64	-4.35***	4.20	1.89	1.22
Average plot area (ha)	0.63	1.19	1.35	8.12	2.29**	0.71	1.52	0.60
Crops provide primary income (%)	68.87	46.33	45.71	50.18	3.96***	45.10	50.25	3.52***
Number of cattle (#)	2.36	6.24	1.21	4.19	1.42	2.92	10.24	-0.53
Soil pH (pH)	6.16	0.47	6.11	0.65	0.73	6.15	0.45	0.13
Soil carbon (%)	3.16	1.51	4.70	1.64	-7.67***	3.32	1.85	-0.65
Soil sand (%)	62.92	13.78	55.43	12.37	4.16***	60.31	12.63	1.20

Appendix 3 Soil Sampling and Analysis

In both survey rounds soil sampling was conducted according to standard protocols for in-field, representative soil sampling. Twelve to twenty sub-samples were taken from each plot, with a thin soil probe that reached down to 20 cm. In plots with very hard soil, occasionally an auger or a hoe was used to collect soil samples, rather than a soil probe. In such cases effort was still made to gather soil down to 20 cm.

Sub-samples were taken from randomly distributed locations around the plot, roughly following zig-zag patterns, but avoiding any "odd" patches of ground such as termite mounds or compost piles. (Soil characteristics associated with such patches may be non-representative of the plot.) After mixing all sub-samples together in a bucket, a representative quantity of 500 grams of soil was gathered for subsequent drying, grinding and analysis.

Soil samples were processed and analyzed at Uganda's National Agricultural Laboratory (NARL), in both 2003 and 2013. In each year they were air dried, ground to pass through a 2-mm sieve, and milled using aluminum or stainless steel grinders.

After grinding, soil sub-samples (roughly 0.5 grams) were analyzed for a number of characteristics. Soil pH was determined in a 2.5:1 water to soil suspension, with the pH measured in the soil suspension after a 30-minute equilibration time (Okalebo et al. 2002). Soil organic carbon was determined via the Walkely-Black method (Walkley and Black 1934). While we believe that the buffer pH changed across 2003 and 2013 for this test, round fixed effects should pick up any difference in mean extraction levels due to this methodological shift. Soil texture, including percentage sand, was determined by hydrometer method in both years, after destruction of organic matter with hydrogen peroxide and dispersion with sodium hexametaphosphate (Bouyoucos 1936; Okalebo et al. 2002).

References

Walkley, Aldous, and I Armstrong Black. 1934. "An examination of the Degtjareff method for determining soil organic matter, and a proposed modification of the chromic acid titration method." Soil Science, 37(1): 29?38.

Okalebo, J Robert, Kenneth W Gathua, and Paul L Woomer. 2002. "Laboratory Methods of Soil and Plant Analysis: A Working Manual." . 2 ed., Chapter Soil Particle Size Analysis by the Bouyoucos or Hydrometer method. Tropical Soil Biology and Fertility Programme Nairobi, Kenya.

Bouyoucos, George John. 1936. "Directions for making mechanical analyses of soils by the hydrometer method." Soil Science, 42(3): 225?230.

Appendix 4 Household-Time Fixed Effects

While this paper's primary results are estimated with plot fixed effects, and controlling for year and season dummies, the same results can be estimated with household-year-season fixed effects. In this case, the identifying variation comes not from within-plot, across-time changes, but rather from cross sectional variation across plots, within a household-year-season group. Fig A2 shows the distribution of the demeaned independent variable plot size, under these two forms of identification. The pooled data variable is given by log plot size, demeaned by household-year-season categories. The panel data variables is given by plot size, demeaned by household-plot categories. The two distributions are clearly quite similar, though a Kolmogorov-Smirnov test for equality of distributions finds them to be significantly different.

Explanatory power is lower when results are estimated via this second form of cross-sectional variation, implying that the plot level fixed effects are a better specification. The coefficients estimated, however, are qualitatively (and quantitatively) the same as those estimated under plot fixed effects, with two exceptions. First, the perimeter-area ratio explains approximately half, but not 100 percent, of the inverse size-productivity relationship, as seen in Tables A6 (analogous to Table 5). Similarly, and the perimeter-area ratio explains approximately half, but not 100 percent, of the inverse size-labor relationship, as seen in Table A7 (analogous to Table 6). Second, farmer perceptions are not as strongly associated with plot productivity in Table A8 as they are in Table 7.

The fact that the inverse relationship remains under household-year-season fixed effects, even once perimeter-area ratio is controlled for, suggests that within households/farms, larger plots are on average less productive than smaller plots. This could conceivably be due to time-invariant, plot-level characteristics that are merely associated with plot size. It could also be causal, driven by mechanisms that impact productivity across plots within households, but not within plots across time. Or, as proposed by Gourlay, Kilic and Lobell (2017) and Desiere and Jolliffe (2017), it may be that farmers over-estimate production on small plots and over-estimate production on large plots, again a phenomenon that would occur farms, but is unlikely to occur across time periods. Notably, whatever the mechanism, it happens alongside the effect of plot perimeter-area ratio, which is still observed to drive both productivity and labor (Columns 2-4 of Tables A6 and A7).

Figure A2: Identifying Variation in Plot Size

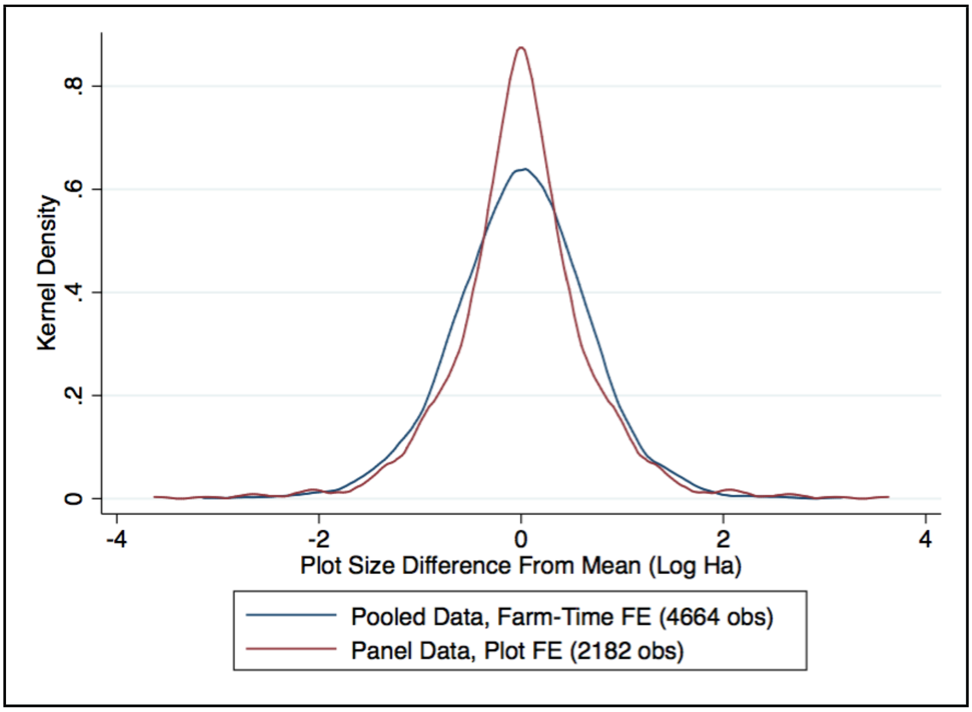


Table A3: Plot Characteristics in 2003 and 2013

	2003		2013		
	Mean or Median†	Standard Deviation	Mean or Median†	Standard Deviation	T Statistic‡
Size, Productivity, Labor					
Farm size (ha)	0.92	1.96	0.61	0.91	22.09***
Plot size (ha)	0.19	1.83	0.18	0.39	4.02***
Perimeter-area ratio (m/ha)	1,093.91	1,071.70	1,117.90	5,141.13	-4.14***
Plot productivity (revenue§/ha)	105.40	1,383.62	247.99	6,948.77	-24.11***
Labor intensity (hrs/ha/day)	2.45	15.08	1.73	53.60	9.02***
Soils					
Soil pH (pH)	6.13	0.60	6.09	0.60	2.27**
Soil sand (%)	60.29	15.11	54.60	15.52	12.96***
Soil organic carbon (%)	3.63	2.03	3.43	1.84	3.58***
Inputs					
Organic amendment (%)	10.54	30.71	8.44	27.80	2.85***
Inorganic fertilizer (%)	1.68	12.85	1.66	12.77	0.07
Irrigation (%)	1.70	12.92	0.31	5.52	5.21***
Terracing (%)	15.43	36.13	6.81	25.19	10.67***
Management					
Head owns plot (%)	61.28	48.72	74.19	43.77	-11.04***
Head manages plot (%)	50.94	50.00	64.39	47.89	-10.96***
(Head owns)X(Head manages)	42.99	49.51	57.76	49.40	-11.96***
Crops are rotated (%)	29.95	45.81	49.40	50.01	-15.30***
Crops are mono-cropped (%)	58.57	49.27	42.43	49.43	13.10***
Mixed cropping (%)	38.05	48.56	44.20	49.67	-5.02***
Intercropping (%)	3.36	18.02	12.96	33.59	-15.17***
Crops Grown					
Tubers grown (%)	40.10	49.02	26.07	43.91	11.93***
Cereals grown (%)	50.54	50.00	50.45	50.01	0.07
Legumes grown (%)	51.58	49.98	44.01	49.65	6.08***
Bananas grown (%)	29.60	45.66	19.07	39.29	9.76***
Cash crops grown (%)	18.30	38.67	15.34	36.04	3.15***

†The first 5 variables are all distributed log-normally, and therefore median is listed and T-statistics are generated using the log variable. For all other variables mean is listed and T-statistics are generated using the variable directly.

‡ *** $p<0.01$, ** $p<0.05$, * $p<0.1$

§ Revenue is given in real, 2005-valued dollars.

Table A4: Measurement Error and the Inverse Relationship (Household-Time FE)

	(1) Plot Productivity	(2) Plot Productivity
Farmer-recalled plot size (log ha)	-0.547***	
	(0.0260)	
GPS-measured plot size (log ha)		-0.565***
		(0.0259)
Observations	5730	4845
Adjusted R^2	0.136	0.170

Col 1 dependent variable: log(revenue/farmer-recalled-hectare)
Col 2 dependent variable: log(revenue/GPS-measured-hectare)
Estimated with household-year-season fixed effects
Household-year-season-clustered standard errors in parentheses
Table estimates Equation 4
p<0.01, ** p<0.05, * p<0.1

Table A5: Omitted Variables and the Inverse Relationship (Household-Time FE)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity	(4) Plot Productivity	(5) Plot Productivity	(6) Plot Productivity
GPS-measured plot size (log ha)	-0.533***	-0.514***	-0.390***	-0.551***	-0.561***	-0.352***
	(0.0309)	(0.0309)	(0.0334)	(0.0305)	(0.0305)	(0.0346)
Soil pH (pH)		-0.856				-1.097**
		(0.557)				(0.526)
Soil pH^2 (pH^2)		0.0955**				0.110**
		(0.0469)				(0.0440)
Soil sand (%)		0.00318				0.00327
		(0.00269)				(0.00259)
Soil organic carbon (%)		0.0270				0.0309*
		(0.0196)				(0.0173)
Labor intensity (log hrs/ha/day)			0.299***			0.344***
			(0.0292)			(0.0304)
Organic amendment (binary)			0.318***			0.0661
			(0.0872)			(0.0892)
Inorganic fertilizer (binary)			1.147***			1.135***
			(0.372)			(0.366)
Irrigation (binary)			0.400			0.530**
			(0.286)			(0.250)
Terracing (binary)			0.363***			0.234**
			(0.0922)			(0.0934)
Head owns plot (binary)				-0.0985		-0.115
				(0.181)		(0.169)
Head manages plot (binary)				0.202		0.166
				(0.174)		(0.161)
(Head owns)X(Head manages)				0.0161		0.0584
				(0.211)		(0.193)
Crops are rotated (%)				-0.333***		-0.375***
				(0.0820)		(0.0843)
Crops are mono-cropped (%)				-0.104		-0.0370
				(0.141)		(0.133)
Mixed cropping (%)				0.153		0.0482
				(0.145)		(0.135)
Tubers grown (binary)					0.277***	0.205***
					(0.0572)	(0.0559)
Cereals grown (binary)					0.00661	-0.0488
					(0.0559)	(0.0560)
Legumes grown (binary)					0.234***	0.114**
					(0.0507)	(0.0546)
Bananas grown (binary)					0.535***	0.354***
					(0.0777)	(0.0801)
Cash crops grown (binary)					0.236***	0.125*
					(0.0737)	(0.0698)
Observations	3472	3472	3472	3472	3472	3472
Adjusted R^2	0.154	0.170	0.241	0.171	0.197	0.295
R^2	0.154	0.171	0.242	0.173	0.198	0.299

Dependent variable: log(revenue/hectare)
All columns estimated using only the sample for Column 6
Estimated with household-year-season fixed effects
Household-year-season-clustered standard errors in parentheses
Table estimates Equation 5
p<0.01, ** p<0.05, * p<0.1

Table A6: Edge Effect and the Inverse Relationship (Household-Time FE)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity	(4) Plot Productivity
GPS-measured plot size (log ha)	-0.565***	-0.304***		-0.802***
	(0.0259)	(0.0604)		(0.0556)
Perimeter-area ratio (log m/ha)		0.499***	0.995***	
		(0.105)	(0.0424)	
Perimeter (log m)				0.499***
				(0.105)
Observations	4845	4845	4845	4845
Adjusted R^2	0.170	0.176	0.169	0.176

Dependent variable: log(revenue/hectare)
Estimated with household-year-season fixed effects
Household-year-season-clustered standard errors in parentheses
Table estimates Equation 10
p<0.01, ** p<0.05, * p<0.1

Table A7: Edge Effect and Labor Intensity (Household-Time FE)

	(1) Labor Intensity	(2) Labor Intensity	(3) Labor Intensity	(4) Labor Intensity
GPS-measured plot size (log ha)	-0.551***	-0.373***		-0.722***
	(0.0228)	(0.0538)		(0.0463)
Perimeter-area ratio (log m/ha)		0.349***	0.976***	
		(0.0894)	(0.0387)	
Perimeter (log m)				0.349***
				(0.0894)
Observations	4575	4575	4575	4575
Adjusted R^2	0.219	0.223	0.209	0.223

Dependent variable: log(hours/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 11
p<0.01, ** p<0.05, * p<0.1

Table A8: The Effects of Farmer Misperception of Plot Size (Household-Time FE)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity
Farmer over-estimates plot (binary)	0.0337	0.0435	0.0779
	(0.0804)	(0.0803)	(0.0917)
Over-estimate (% area)	0.0704***	0.0739***	0.0320
	(0.0204)	(0.0208)	(0.0249)
Over-estimate squared	-0.00151**	-0.00203***	-0.00115
	(0.000672)	(0.000734)	(0.000869)
Under-estimate (% area)	-0.365	-0.336	-0.106
	(0.460)	(0.461)	(0.544)
Under-estimate squared	-0.329	-0.390	-0.284
	(0.560)	(0.565)	(0.659)
Plot Area, P-A Ratio	Yes	Yes	Yes
$(\text{Area})^2$, $(\text{P-A Ratio})^2$	No	Yes	Yes
Additional Plot Controls	No	No	Yes
Observations	4845	4845	3472
Adjusted R^2	0.190	0.192	0.301

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Additional plot controls are from Column 6 of Table 3
Table estimates Equation 12
p<0.01, ** p<0.05, * p<0.1

Appendix 5 Plot Size Change Over Time

Plots, defined as an area of land with a continuous cropping system, are situated on parcels. A parcel is a contiguous piece of land under one form of ownership, and in our pooled dataset of all plots from all time periods, parcels have between 1 and 10 plots on them. Fifty percent of our 2003 plots come from a parcel that holds only that single plot — this figure is 57 percent in 2013. The average plot in 2003 is on a parcel that holds 2 plots, and the average plot in 2013 is on a parcel that holds 1.8 plots.

Between 2003 and 2013, 32 percent of plots grew and 68 percent of plots shrank — but the majority of this variation is not driven by parcel-level divisions or changes. Indeed, in our full dataset of 2013 plots, only 7 percent sit on a parcel that experienced sub-division between 2003 and 2013. This is despite the fact that 21 percent of houses did sub-divide at least 1 parcel over the decade, and 40 percent of households either lost an entire parcel over the decade or lost a sub-division of a parcel. (Seventy percent of land disposition, including both entire parcels being lost and parcel sub-divisions being lost, is done for the purpose of land sale or land gift/bequeathment.)

Rather, the primary predictor of plot size change (change in plot hectares between 2003 and 2013) is starting plot size in 2003. This is illustrated by Figure A3. Plots that were larger in 2003 are more likely to shrink over the decade. Contingent on shrinking, they also shrink more. (Though conversely, for plots that grow over time, 2003 size is positively correlated with how much they grow.) While it seems plausible that plots belonging to households who lost a parcel, or plots situated on parcels that experienced sub-division, might shrink more than other plots, Figure A4 suggests that this may not be the case. The univariate, non-parametric relationship between starting plot size and plot size change is the same across (i) all pots, (ii) plots belonging to households who lost a parcel, and (iii) plots situated on parcels that experienced sub-division. (However, this figure also illustrates that plots on parcels that experience subdivision generally started out larger in 2003 than other plots.)

Table A9 examines correlates with plot size change — the logarithm of the difference between plot size in 2013 and plot size in 2003 — via a multiple regression framework. In Columns 1-4 plot size change is estimated as a function of 2003 covariates only, one observation per plot, by simple OLS. (For continuous covariates observed in both seasons of 2003 an average is used, and for binary covariates observed in both seasons of 2003 the maximum value is used.) In Columns 5-8 plot size change is again estimated as a function of 2003 covariates, but including household fixed effects. Under both identification strategies (i.e., whether viewing variation across all plots or across plots within households), the strongest predictor of plot size change is 2003 plot size. Neither parcel subdivision nor the household-level loss of a parcel is significantly associated with plot size change, as suggested by Figure A4.

Yet, in Column 7 we do observe a negative effect of both parcel sub-division and parcel sub-division interacted with plot size. Figure A5 displays a similar effect graphically — the variable being graphed is plot size change demeaned by household, and while 2003 plot size is negatively associated with (demeaned) plot size change for all plots, this is particularly true for those plots on subdivided parcels. The confidence intervals also make it clear, however, why the effect is not statistically significant.

Figure A3: Plot Size Change by 2003 Plot Size

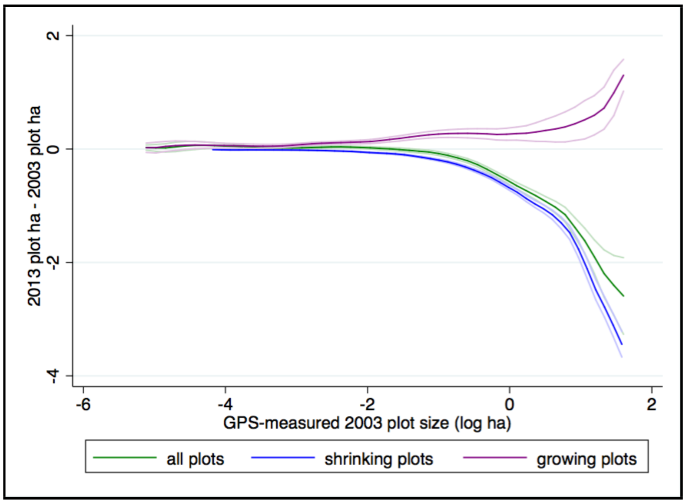


Figure A4: Plot Size Change by Parcel Occurrences

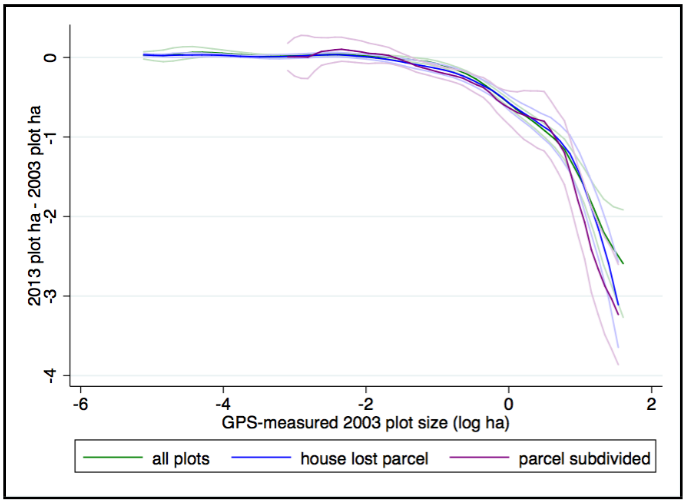


Figure A5: Plot Size Change by 2003 Plot Size (Deviation from Household Mean)

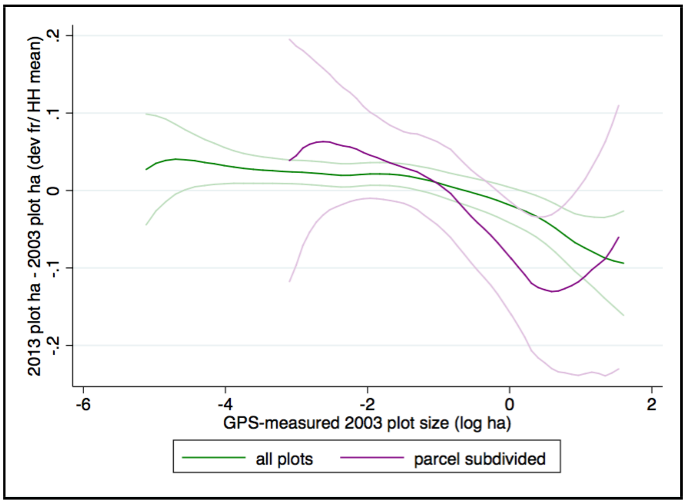


Table A9: Correlates of Plot Size Change in Geospatially-Matched Plots (OLS)

	OLS				Household Fixed Effects			
	(1) Plot Size Change	(2) Plot Size Change	(3) Plot Size Change	(4) Plot Size Change	(5) Plot Size Change	(6) Plot Size Change	(7) Plot Size Change	(8) Plot Size Change
GPS-measured plot size '03 (log ha)	-0.498***		-0.496***	-0.502***	-0.600***		-0.529***	-0.422***
	(0.0441)		(0.0705)	(0.0724)	(0.0702)		(0.0961)	(0.126)
Plot on a sub-divided parcel (binary)		-0.391	-0.0697	0.350		-0.777***	-0.234	0.672
		(0.253)	(0.322)	(0.236)		(0.218)	(0.359)	(0.502)
(Plot size '03)x(Lost parcel/sub-division)			-0.0856	0.0627			0.0853	0.390*
			(0.179)	(0.127)			(0.174)	(0.210)
At least 1 parcel/division was lost (binary)		0.0240	-0.139	-0.204				
		(0.132)	(0.192)	(0.197)				
(Plot size '03)x(Sub-divided parcel)			0.0206	-0.00560			-0.0917	-0.102
			(0.0911)	(0.0930)			(0.158)	(0.163)
Soil pH (pH)				2.775**				3.877*
				(1.170)				(1.986)
Soil pH^2 (pH^2)				-0.224**				-0.301*
				(0.0991)				(0.167)
Soil sand (%)				-0.00204				0.00656
				(0.00353)				(0.00601)
Soil organic carbon (%)				0.0298				-0.0512
				(0.0273)				(0.0616)
Labor intensity (log hrs/ha/day)				-0.0731				0.107
				(0.0487)				(0.0878)
Organic amendment (binary)				-0.0998				-0.145
				(0.127)				(0.184)
Inorganic fertilizer (binary)				-1.638				0
				(1.224)				(.)
Irrigation (binary)				0.298				-0.0694
				(0.279)				(0.369)
Terracing (binary)				0.254*				0.0794
				(0.130)				(0.245)
Head owns plot (binary)				0.234*				0.173
				(0.137)				(0.567)
Head manages plot (binary)				0.248				-0.572*
				(0.173)				(0.311)
(Head owns)X(Head manages)				-0.523**				0.428
				(0.211)				(0.824)
Crops are rotated (%)				0.0596				0.0730
				(0.119)				(0.179)
Crops are mono-cropped (%)				-0.168				-0.271
				(0.169)				(0.219)
Mixed cropping (%)				-0.0989				0.126
				(0.182)				(0.207)
Tubers grown (binary)				-0.309***				-0.107
				(0.113)				(0.175)
Cereals grown (binary)				-0.148				-0.221
				(0.108)				(0.144)
Legumes grown (binary)				0.105				0.0432
				(0.127)				(0.171)
Bananas grown (binary)				-0.109				-0.124
				(0.160)				(0.203)
Cash crops grown (binary)				-0.135				-0.235
				(0.125)				(0.176)
Observations	738	656	656	552	738	657	656	552
Adjusted R^2	0.260	0.005	0.253	0.315	0.197	0.004	0.175	0.194

Dependent variable: log([2013 revenue/hectare] - [2003 revenue/hectare])
All covariates are from round 1 (R1) of the geospatially matched panel dataset
Columns 1-4 estimated via OLS; Columns 4-5 estimated via household fixed effects
Household-clustered standard errors in parentheses for all columns
*** p<0.01, ** p<0.05, * p<0.1

Appendix 6 Selection into Datasets

1. Selection into Geospatially-Matched Plot Panel

Our primary estimations are performed in a plot panel under plot fixed effects. Plots are geospatially matched across the decade using GPS. Plots that cannot be matched across the decade are therefore dropped, and household with no geospatially matched plots are not included in the dataset. Twenty-eight percent of 2003 households and 34 percent of 2003 plots appear in the panel dataset; forty-four percent of 2013 households and 30 percent of 2013 plots appear in the panel dataset.

It seems likely that selection into the geospatially-matched dataset is not random. Tables A10 and A11 therefore compare household and plot characteristics across (i) the universe of all households/plots from 2003 and 2013, and (ii) the households/plots in the geospatially-matched plot-level panel dataset. In Table A10 the unit of observation is the household, while in Table A11 the unit of observation is the plot.

Table A10 suggests that 2003 households select into the panel dataset in a fairly random manner — on the whole, the datasets seem similar at the household level, though the households in the panel dataset have slightly fewer plots owned, on average, and slightly larger household sizes. The 2013 households that end up in the panel dataset have very slightly older household heads than the households in the larger 2013 dataset, and are further from roads. All other household-level characteristics are balanced across datasets.

The plot level selection is far less random, in both rounds. Table A11 shows that larger 2003 plots end up in the panel dataset; 2003 plots growing bananas or cash crops were also more likely to end up in the panel dataset. Soil quality, inputs and management also differ across the universe of all 2003 plots and the 2003 plots that end up in the panel dataset.

Table A10: Universe of All Households vs Plot FE Model Households

	2003			2013		
	Universe	Plot FE	T-stat	Universe	Plot FE	T-stat
Farm size (ha)	1.26	1.26	-0.68	0.69	0.66	0.15
Number of plots owned (#)	4.69	4.41	1.64	4.15	4.11	0.33
Number of crops grown (#)	5.85	5.99	-0.83	3.41	3.51	-0.90
Head years of education (#)	4.94	4.84	0.39	5.45	5.23	0.92
Head age (#)	41.50	43.39	-1.85*	49.53	51.37	-2.04**
Household size (# people)	5.86	6.32	-2.13**	6.46	6.08	1.77*
Asset index (index)	14.00	14.14	-1.88*	13.34	13.42	-1.22
Net crop income (1,000 Ush)	527.75	529.16	-2.07**	746.48	820.83	-0.95
Distance to all weather road (km)	2.51	2.42	0.20	5.66	4.82	2.04**
Distance to market (km)	3.14	2.83	1.04	4.68	5.13	-0.58

Table A11: Universe of All Plots vs Plot FE Model Plots

	2003			2013		
	Universe	Plot FE	T-stat	Universe	Plot FE	T-stat
Plot size (ha)	0.40	0.48	-5.56***	0.30	0.31	0.29
Perimeter-area ratio (m/ha)	1,375.42	1,190.42	5.14***	1,759.60	1,796.13	0.02
Plot productivity (revenue/ha)	324.62	291.09	1.40	1,006.35	1,139.03	-0.68
Labor intensity (hrs/ha/day)	5.19	4.34	2.49**	6.79	9.07	-1.09
Soil pH (pH)	6.11	6.19	-2.95***	6.06	6.12	-2.03**
Soil sand (%)	60.92	60.30	0.83	55.52	53.37	2.89***
Soil organic carbon (%)	3.55	3.44	1.16	3.33	3.64	-3.63***
Organic amendment (%)	8.94	17.12	-6.01***	7.28	10.16	-2.41**
Inorganic fertilizer (%)	1.69	1.27	0.75	1.80	1.63	0.31
Irrigation (%)	1.67	1.44	0.39	0.29	0.14	0.68
Terracing (%)	14.48	22.66	-5.03***	6.27	9.24	-2.63***
Head owns plot (%)	59.87	66.09	-2.87***	75.30	74.93	0.19
Head manages plot (%)	50.22	54.20	-1.79*	63.79	63.69	0.05
(Head owns)X(Head manages)	42.45	45.48	-1.38	57.13	58.94	-0.84
Crops are rotated (%)	30.49	24.51	2.91***	51.60	45.73	2.41**
Crops are mono-cropped (%)	59.95	47.23	5.81***	47.15	41.06	2.80***
Mixed cropping (%)	36.05	49.76	-6.37***	39.59	47.56	-3.69***
Tubers grown (%)	40.21	42.79	-1.18	26.34	25.61	0.38
Cereals grown (%)	49.35	48.65	0.31	49.86	44.72	2.35**
Legumes grown (%)	49.98	51.98	-0.90	41.68	43.63	-0.90
Bananas grown (%)	24.32	42.16	-9.06***	16.13	24.12	-4.72***
Cash crops grown (%)	16.24	27.42	-6.52***	13.71	17.21	-2.26**

2. Selection into Pooled Dataset under Household-Time Fixed Effects
We additionally estimate all core results using pooled data from both 2003 and 2013, via a household-year-season fixed effect model. Rather than identifying via within-plot, over-time variation, this household-time fixed effect model identifies via across-plot, within-time variation. There is also selection into this dataset, however, as all household-rounds with only 1 plot are dropped from the estimation. In 2003 and 2013, 16 percent and 32 percent percent of households, respectively, had only 1 plot. These households are thus dropped from the dataset for estimation, along with their 1 plot each — 5 and 14 percent of the total universe of plots, in 2003 and 2013 respectively.

Households with only one plot might be different than households with multiple plots, in any number of ways. If so, the houses/plots used for household-time fixed effect analysis might not be representative of the larger universe of houses/plots that we view in our data. As we would expect, Table A12 shows that 2003 households who make it into the household-time fixed effect analysis more plots than the larger group of 2003 households — 0.38 more plots, on a average — though also slightly smaller farms. The 2013 households who make it into this analysis also have more plots — 0.5 more plots, on average — and have larger farms. In both years, the households included in household-time fixed effect analysis have slightly higher levels of crop income than households in the larger universe of data.

Interestingly, Table A13 suggests that plot-level selection into the household-time fixed effect dataset is random. No significant difference exists between the plots that end up in this dataset and the larger universe of all pooled plots, in either 2003 or 2013.

Table A12: Universe of All Households vs HH-Time FE Model Households

	2003			2013		
	Universe	HH-time FE	T-stat	Universe	HH-time FE	T-stat
Farm size (ha)	1.26	1.21	-1.80*	0.69	0.85	-5.82***
Number of plots owned (#)	4.69	5.07	-3.10***	4.15	4.75	-4.91***
Number of crops grown (#)	5.85	6.13	-2.55**	3.41	3.90	-5.26***
Head years of education (#)	4.94	5.03	-0.50	5.45	5.41	0.21
Head age (#)	41.50	41.37	0.18	49.53	49.96	-0.56
Household size (# people)	5.86	5.97	-0.75	6.46	6.72	-1.41
Asset index (index)	14.00	14.02	-0.52	13.34	13.38	-0.80
Net crop income (1,000 Ush)	527.75	559.25	-1.84*	746.48	826.69	-2.37**
Distance to all weather road (km)	2.51	2.40	-0.00	5.66	5.14	0.69
Distance to market (km)	3.14	3.17	-0.29	4.68	4.88	-0.38

Table A13: Universe of All Plots vs HH-Time FE Model Plots

	2003			2013		
	Universe	HH-time FE	T-stat	Universe	HH-time FE	T-stat
Plot size (ha)	0.40	0.34	1.29	0.30	0.30	-0.08
Perimeter-area ratio (m/ha)	1,375.42	1,397.59	-1.10	1,759.60	1,768.43	0.16
Plot productivity (revenue/ha)	324.62	334.36	-0.49	1,006.35	1,061.54	-0.14
Labor intensity (hrs/ha/day)	5.19	5.30	-0.55	6.79	7.06	0.06
Soil pH (pH)	6.11	6.09	0.53	6.06	6.06	0.16
Soil sand (%)	60.92	60.80	0.23	55.52	55.32	0.34
Soil organic carbon (%)	3.55	3.59	-0.48	3.33	3.32	0.17
Organic amendment (%)	8.94	8.61	0.41	7.28	6.56	0.81
Inorganic fertilizer (%)	1.69	1.53	0.43	1.80	1.57	0.51
Irrigation (%)	1.67	1.67	-0.02	0.29	0.33	-0.24
Terracing (%)	14.48	14.49	-0.02	6.27	6.43	-0.18
Head owns plot (%)	59.87	59.25	0.44	75.30	75.08	0.14
Head manages plot (%)	50.22	49.86	0.25	63.79	63.28	0.30
(Head owns)X(Head manages)	42.45	42.11	0.24	57.13	57.05	0.05
Crops are rotated (%)	30.49	30.82	-0.25	51.60	52.80	-0.62
Crops are mono-cropped (%)	59.95	61.08	-0.81	47.15	48.92	-1.01
Mixed cropping (%)	36.05	35.03	0.75	39.59	37.77	1.07
Tubers grown (%)	40.21	39.01	0.87	26.34	26.03	0.20
Cereals grown (%)	49.35	48.03	0.93	49.86	49.31	0.31
Legumes grown (%)	49.98	48.99	0.70	41.68	39.21	1.44
Bananas grown (%)	24.32	23.93	0.32	16.13	15.93	0.15
Cash crops grown (%)	16.24	15.78	0.45	13.71	13.90	-0.16

Appendix 7 Perimeter-Area Ratio by Plot Shape

Rather than assuming a generically shaped plot, we can assume plots of various, specific plot shapes in order to show more quantitatively that, with a small border width b, plot productivity Y_{ij} will always increase in P_{ijt}/A_{ij}, where P_{ijt} is the perimeter of the plot and A_{ijt} is the area of the plot. For the following calculations, we drop the ij subscript for all variables, for simplicity in notation. In all cases therefore, we define average productivity of the plot in question as below, exactly as in Equation 7.

$$Y \equiv \frac{Y^I * A^I + Y^P * A^P}{A}$$

Circle

Assume a circular plot with radius R, diameter D, border width b, perimeter $P = 2\pi R$ and total area $A = \pi R^2$. The interior of the plot has area $A^I = \pi(R-b)^2$, and the periphery, or border area, of the plot has area $A^P = A - A^I$. These area definitions can be expanded as follows.

$$A^I = \pi(R^2 - 2bR + b^2) = \pi R^2 - 2\pi bR + \pi b^2$$

$$A^P = (\pi R^2) - (\pi R^2 - 2\pi bR + \pi b^2) = 2\pi bR - \pi b^2$$

Average productivity can therefore be re-written as below.

$$\begin{aligned}
Y &= \frac{1}{A}(\pi R^2 - 2\pi bR + \pi b^2)Y^I + \frac{1}{A}(2\pi bR - \pi b^2)Y^P \\
&= \frac{1}{A}(2\pi bR - \pi b^2)(Y^P - Y^I) + \frac{1}{A}(\pi R^2)Y^I \\
&= \frac{1}{A}(2\pi bR)(Y^P - Y^I) - \frac{1}{A}(\pi b^2)(Y^P - Y^I) + \frac{1}{A}(A)Y^I \\
&= \frac{1}{A}bP(Y^P - Y^I) - \frac{1}{A}(\pi b^2)(Y^P - Y^I) + Y^I \\
&= \left[Y^I\right] + b(Y^P - Y^I)\left[\frac{P}{A}\right] - (\pi b^2)(Y^P - Y^I)\left[\frac{1}{A}\right]
\end{aligned}$$

Average productivity is therefore expected to rise with $\frac{P}{A}$ and to fall with $\frac{1}{A}$. However, if we assume that b is so small that b^2/A is close to zero, the last term of the equation disappears, and we expect productivity to rise only with $\frac{P}{A}$.

Rectangle

Assume a rectangular plot with length L and width W, border width b, perimeter $P = 2L + 2W$ and total area $A = WL$. The interior of the plot has area $A^I = (W - 2b)(L - 2b)$, and the periphery of the plot has area $A^P = A - A^I$. These area definitions can be expanded as follows.

$$A^I = WL - 2Wb - 2Lb + 4b^2$$

$$A^P = WL - (WL - 2Wb - 2Lb + 4b^2) = 2Wb + 2Lb - 4b^2$$

Average productivity can therefore be re-written as below.

$$
\begin{aligned}
Y &= \frac{1}{A}(WL - 2Wb - 2Lb + 4b^2)Y^I + \frac{1}{A}(2Wb + 2Lb - 4b^2)Y^P \\
&= \frac{1}{A}(2Wb + 2Lb - 4b^2)(Y^P - Y^I) + \frac{1}{A}(WL)Y^I \\
&= \frac{1}{A}(2Wb + 2Lb)(Y^P - Y^I) - \frac{1}{A}(4b^2)(Y^P - Y^I) + \frac{1}{A}(A)Y^I \\
&= \frac{1}{A}b(P)(Y^P - Y^I) - \frac{1}{A}(4b^2)(Y^P - Y^I) + Y^I \\
&= \left[Y^I\right] + b(Y^P - Y^I)\left[\frac{P}{A}\right] - (4b^2)(Y^P - Y^I)\left[\frac{1}{A}\right]
\end{aligned}
$$

Average productivity is therefore expected to rise with $\frac{P}{A}$ and to fall with $\frac{1}{A}$. However, if we assume that d is so small that b^2/A is close to zero, the last term of the equation disappears, and we expect productivity to rise only with $\frac{P}{A}$.

Triangle

Assume an equilateral triangular plot with each side being length S, border width b, perimeter P= $3S$ and total area A= $\frac{\sqrt{3}}{4}S^2$. The interior of the plot has area $A^I = \frac{\sqrt{3}}{4}(S - 2\sqrt{3}b)^2$, and the periphery of the plot has area A^P= $A - A^I$. These area definitions can be expanded as follows.

$$
A^I = \frac{\sqrt{3}}{4}\left[S^2 - 4\sqrt{3}bS + 12b^2\right] = \frac{\sqrt{3}}{4}S^2 - 3bS + 3\sqrt{3}b^2
$$

$$
A^P = \frac{\sqrt{3}}{4}S^2 - \left[\frac{\sqrt{3}}{4}S^2 - 3bS + 3\sqrt{3}b^2\right] = 3bS - 3\sqrt{3}b^2
$$

Average productivity can therefore be re-written as below.

$$
\begin{aligned}
Y &= \frac{1}{A}\left[\frac{\sqrt{3}}{4}S^2 - 3bS + 3\sqrt{3}b^2\right]Y^I + \frac{1}{A}\left[3bS - 3\sqrt{3}b^2\right]Y^P \\
&= \frac{1}{A}\left[3bS - 3\sqrt{3}b^2\right](Y^P - Y^I) + \frac{1}{A}\left[\frac{\sqrt{3}}{4}S^2\right]Y^I \\
&= \frac{1}{A}\left[3bS\right](Y^P - Y^I) - \frac{1}{A}\left[3\sqrt{3}b^2\right](Y^P - Y^I) + \frac{1}{A}(A)Y^I \\
&= \frac{1}{A}b(P)(Y^P - Y^I) - \frac{1}{A}\left[3\sqrt{3}b^2\right](Y^P - Y^I) + Y^I \\
&= \left[Y^I\right] + b(Y^P - Y^I)\left[\frac{P}{A}\right] - (3\sqrt{3}b^2)(Y^P - Y^I)\left[\frac{1}{A}\right]
\end{aligned}
$$

Average productivity is therefore expected to rise with $\frac{P}{A}$ and to fall with $\frac{1}{A}$. However, if we assume that d is so small that b^2/A is close to zero, the last term of the equation disappears, and we expect productivity to rise only with $\frac{P}{A}$.

What if the periphery is wide?

In all three of these specifications, we see that Y rises linearly with $b(Y^P - Y^I)[P/A]$, and falls linearly with $gb^2(Y^P - Y^I)[1/A]$, where g is a scaling factor that varies by plot shape. For circles, $g = \pi \approx 3.142$, for rectangles $g = 4$, and for equilateral triangles $g = 3\sqrt{3} \approx 5.196$. (So, it appears that g falls as the number of sides increases.)

Therefore, under each of these three specifications, if the width of the periphery/border length b is so very narrow that b^2/A is close to zero, we would expect to find that average plot productivity Y rises only with P/A. If the periphery length b is wide, however, we expect that average plot productivity rises with P/A and also falls with $1/A$.

However, when we do these regressions in practice, we regress the log form of these variables — so we would regress $log(Y)$ on $log(P/A)$ and $log(1/A)$. But $log(1/A)$ $= log(A^{-1}) = -1 * log(A)$. So if the periphery length b is wide, we expect that average plot productivity both rises only with $log(P/A)$ and also rises with $log(A)$. Increasing with $log(A)$ is equivalent to decreasing with $log(1/A)$.

In Table 5, however, we find that plot area has no additional, explanatory power after perimeter-area ratio is controlled for. This suggests that, indeed, periphery length b is narrow enough that in most cases we can assume that b^2/A is close to zero.

Appendix 8 More on Edge Effect Mechanisms

It seems feasible that both biophysical and behavioral mechanisms drive the edge effect, but we have limited ability to test either hypothesis. Table 6 provides some evidence that farmers provide more labor to plots with a higher ratio of peripheral area, suggesting that labor allocation may play into the edge effect. Below, we provide some further analysis regarding labor inputs as a mechanism. Second, we indirectly test for biophysical mechanisms as best as possible given that we have no data on biophysical inputs.

Behavioral Mechanisms

Table A14 illustrates that the edge effect is statistically identical across family and non-family labor, though it becomes slightly smaller in magnitude and insignificant for non-family labor. Likely, however, this is due to a reduced sample size. (In Uganda, both hired labor and exchange labor are relatively rare.) Table A15 estimates the edge effect by various labor tasks. It appears that edge effect most strongly drives weeding and planting labor. The result is difficult to interpret, however, because the third category of "other labor" includes labor allocated towards a litany of other tasks, none of which account for any significant proportion of total labor across households. All in all, little can be gleaned in these data about how the edge effect might vary by types of labor or laborers.

Biophysical Mechanisms

First, if soil nutrients are more plentiful at the edges of a plot, therefore driving these edges to be more productive, then we might expect the edge effect to function most strongly in nutrient-constrained settings. We therefore modify Equation 10 to control for plot-specific soil quality S_{ijt} and interactions between soil quality and the perimeter-area ratio, as in Equation 13 below. If $\hat{\theta}$ reduces in magnitude and $\hat{\eta}$ is significant and negative, this indicates that the edge effect is particular strong in nutrient-constrained settings.

$$Y_{ijt} = \gamma A_{ijt} + \theta \frac{P_{ijt}}{A_{ijt}} + \zeta S_{ijt} + \eta \left[\frac{P_{ijt}}{A_{ijt}} * S_{ijt} \right] \tag{13}$$

Table A16 below shows results for Equation 13, specifying soil fertility in three ways — by soil organic matter, soil sand content, and soil nitrogen. In all cases, the coefficient on the perimeter-area ratio is unchanged, and the coefficient on the interaction between soil fertility and the ratio is insignificant. While this result does not, of course, prove that soil fertility gradients do *not* drive the gradient, it also does not support nutrient availability as an edge effect mechanism.

Second, if differential access to sunlight drives the edges of a plot to be more productive, then we might expect the edge effect to function most strongly with taller plants such as maize, millet, or sesame, where the plants around plot edges likely block sunlight from the plants in the interior. For crops grown close to the ground, such as groundnuts or potatoes, we might expect the edge effect to be weaker. Table A17 therefore estimates Equation 10 for subsets of plots according to crop height. The edge effect is identical for tall crops (Column 2) and for ground crops (Column 3), a finding that does not support sunlight as the mechanism behind the edge effect. Interestingly, the edge effect is smaller and insignificant for tree crops (bananas, cassava and coffee). Because tree crops differ from seasonal crops in terms of management, labor, biophysical inputs and more customary inputs, it is difficult to interpret this result.

Third, Ward, Roe and Batte (2016) suggest that the edge effect is stronger in intercropped systems than in monocropped systems, and imply that this effect is due to spacing and light. Table A18 therefore estimates Equation 10 for all plots in Column 1, for plots that are monocropped (according to the farmer) in Column 2, and for plots that are intercropped or contain mixed crops in Column 3. While the magnitude of the coefficient on perimeters-area ratio does rise for mixed cropped and intercropped plots, the difference is not statistically significant.

Table A14: Edge Effect and Labor Intensity by Labor Type (Plot Panel)

	(1) Labor Intensity (All)	(2) Labor Intensity (Family)	(3) Labor Intensity (Non-Family)
Perimeter-area ratio (log m/ha)	1.098***	1.066***	0.652***
	(0.0957)	(0.107)	(0.182)
Observations	2080	2044	789
Adjusted R^2	0.183	0.162	0.076

Dependent variable: log(hours/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 11 for data subsets
p<0.01, ** p<0.05, * p<0.1

Table A15: Edge Effect and Labor Intensity by Labor Type (Plot Panel)

	(1) Labor Intensity (All)	(2) Labor Intensity (Weeding)	(3) Labor Intensity (Planting)	(4) Labor Intensity (Other)
Perimeter-area ratio (log m/ha)	1.098***	1.178***	1.388***	0.685***
	(0.0957)	(0.101)	(0.101)	(0.164)
Observations	2080	1873	1401	1368
Adjusted R^2	0.183	0.231	0.284	0.056

Dependent variable: log(hours/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 11 for data subsets
p<0.01, ** p<0.05, * p<0.1

Table A16: Edge Effect and Soil Nutrients (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity	(4) Plot Productivity
Perimeter-area ratio (log m/ha)	1.076***	1.205***	1.024***	1.139***
	(0.0963)	(0.182)	(0.388)	(0.169)
Soil organic carbon (%)		0.324		
		(0.249)		
(Soil organic carbon)X(Perimeter-area ratio)		-0.0465		
		(0.0342)		
Soil sand (%)			-0.00759	
			(0.0454)	
(Soil sand)X(Perimeter-area ratio)			0.000578	
			(0.00645)	
Soil nitrogen (%)				1.642
				(2.807)
(Soil nitrogen)X(Perimeter-area ratio)				-0.326
				(0.386)
Observations	2189	1898	1898	1898
Adjusted R^2	0.383	0.376	0.374	0.377

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 13
*** p<0.01, ** p<0.05, * p<0.1

Table A17: Edge Effect and Sunlight (Plot Panel)

	(1) Plot Productivity (All Crops)	(2) Plot Productivity (High Crops)	(3) Plot Productivity (Low Crops)	(4) Plot Productivity (Tree Crops)
Perimeter-area ratio (log m/ha)	1.076***	1.512***	1.567***	0.809***
	(0.0963)	(0.123)	(0.178)	(0.116)
Observations	2189	991	528	1290
Adjusted R^2	0.383	0.472	0.365	0.284

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 3 for plot subsets
*** p<0.01, ** p<0.05, * p<0.1

Table A18: Edge Effect and Biodiversity (Plot Panel)

	(1) Plot Productivity (All Plots)	(2) Plot Productivity (Monocropped)	(3) Plot Productivity (Mixed or Intercropped)
Perimeter-area ratio (log m/ha)	1.076***	1.103***	1.244***
	(0.0963)	(0.134)	(0.131)
Observations	2189	1118	1308
Adjusted R^2	0.383	0.386	0.435

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 3 for plot subsets
*** p<0.01, ** p<0.05, * p<0.1

Appendix 9 Inverse Relationship Robustness

Several robustness checks confirm that the plot-level inverse relationship holds across rounds, across data-subsets, and (qualitatively) across functional forms. Table A19 estimates the relationship with household-year-season fixed effects for round 1 only (Column 1), for Round 2 only (column 2) and for both rounds, as in Panel 2 of Table 2. The inverse relationship is larger in magnitude for round 2, but in both years the relationship is strongly, statistically significant and of a magnitude comparable to previous studies. Tables A20 and A21 illustrate that the inverse relationship is fairly stable in magnitude across crop subsets and across managers and agricultural management styles.

Columns 2 and 3 of Table A22 shows that while some plots are growing across time and some plots are shrinking across time, the inverse relationship is estimated for both categories of change. Column 4 shows that while some 2013 plots are matched to multiple 2003 plots, the inverse relationship is statistically identical if we restrict the sample to only those plots that are matched one-to-one, across the decade.

Table A23 illustrates that the inverse relationship, typically estimated via logged variables since both land size (hectares) and productivity (revenue per hectare) are distributed log normally, can also be estimated via other functional forms. In Panel 1, log revenue per hectare is regressed on non-log versions of land size — as with the traditional version of this regression, we see that plot size drives the inverse relationship, not farm size. Because taking the log of a variable is a non-linear transformation, Panel 2 runs the same regression but including squared terms. These terms increase explanatory power (though not to the level achieved by logged variables), and results again confirm that plot size drives the inverse relationship rather than farm size. Panels 3 and 4 hold the same covariates, but use revenue per hectare rather than logged revenue per hectare as the dependent variable. Though statistical significance is lost on all variables, the inverse relationships still holds, and more importantly farm size again adds no additional information, conditional on knowing plot size.

Table A19: The Inverse Relationship by Round (HH-Time FE)

	(1) Plot Productivity (2003 only)	(2) Plot Productivity (2013 only)	(3) Plot Productivity (2003 & 2013)
Plot size (log ha)	-0.476***	-0.686***	-0.565***
	(0.0351)	(0.0358)	(0.0259)
Observations	2804	2041	4845
Adjusted R^2	0.118	0.259	0.170

Dependent variable: log(revenue/hectare)
Estimated with household-year-season fixed effects
Household-year-season-clustered standard errors in parentheses
Table estimates Equation 2 for data subsets by round
p<0.01, ** p<0.05, * p<0.1

Table A20: The Inverse Relationship by Crop (Plot Panel)

	(1) Plot Productivity (All Plots)	(2) Plot Productivity (Tubers)	(3) Plot Productivity (Cereal)	(4) Plot Productivity (Legumes)	(5) Plot Productivity (Banana)	(6) Plot Productivity (Cash Crops)
Plot size (log ha)	-0.621***	-0.621***	-0.892***	-0.495***	-0.447***	-0.572***
	(0.0636)	(0.134)	(0.102)	(0.104)	(0.0940)	(0.196)
Observations	2181	744	1015	1071	831	544
Adjusted R^2	0.381	0.299	0.457	0.335	0.283	0.300

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 2 for data subsets by crop
p<0.01, ** p<0.05, * p<0.1

Table A21: The Inverse Relationship by Ownership/Management (Plot Panel)

	(1) Plot Productivity (Head Owns)	(2) Plot Productivity (Head Manages)	(3) Plot Productivity (Owns & Manages)	(4) Plot Productivity (Crops Rotated)	(5) Plot Productivity (Mono-Cropped)	(6) Plot Productivity (Mixed Cropping)
Plot size (log ha)	-0.632***	-0.482***	-0.536***	-0.766***	-0.645***	-0.814***
	(0.0971)	(0.0688)	(0.0736)	(0.208)	(0.131)	(0.108)
Observations	1551	1298	1154	610	872	1162
Adjusted R^2	0.388	0.330	0.336	0.260	0.360	0.451

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 2 for data subsets by ownership/management
p<0.01, ** p<0.05, * p<0.1

Table A22: The Inverse Relationship by Plot Change Categories (Plot Panel)

	(1) Plot Productivity (All)	(2) Plot Productivity (Shrunk)	(3) Plot Productivity (Grew)	(4) Plot Productivity (Single-Matched)
Plot size (log ha)	-0.621***	-0.770***	-0.429**	-0.660***
	(0.0636)	(0.0828)	(0.215)	(0.0731)
Observations	2181	1531	650	1508
Adjusted R^2	0.381	0.463	0.110	0.437

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 2 for data subsets
p<0.01, ** p<0.05, * p<0.1

Table A23: The Inverse Relationship under Various Functional Forms (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity
	Panel 1: Log Productivity, Linear		
Farm size (ha)	-0.120*		0.0246
	(0.0667)		(0.0543)
Plot size (ha)		-0.603***	-0.621***
		(0.120)	(0.125)
Observations	2181	2181	2181
Adjusted R^2	0.262	0.287	0.286
	Panel 2: Log Productivity, Non-Linear		
Farm size (ha)	-0.442***		-0.0862
	(0.115)		(0.115)
(Farm size)^2	0.0498***		0.0157
	(0.0128)		(0.0123)
Plot size (ha)		-1.292***	-1.242***
		(0.269)	(0.279)
(Plot size)^2		0.218***	0.205**
		(0.0825)	(0.0832)
Observations	2181	2181	2181
Adjusted R^2	0.269	0.300	0.300
	Panel 3: Productivity, Linear		
Farm size (ha)	-77.93		128.5
	(89.99)		(78.28)
Plot size (ha)		-794.9	-890.0
		(557.4)	(601.5)
Observations	2182	2182	2182
Adjusted R^2	0.011	0.014	0.014
	Panel 4: Productivity, Non-Linear		
Farm size (ha)	-735.4		-65.11
	(529.5)		(168.4)
(Farm size)^2	101.5		26.84
	(71.12)		(25.52)
Plot size (ha)		-2876.8	-2849.0
		(1921.0)	(1889.4)
(Plot size)^2		657.8	634.2
		(445.7)	(431.2)
Observations	2182	2182	2182
Adjusted R^2	0.013	0.021	0.020

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot clustered standard errors in parentheses
Table estimates equations similar to Equation 2
*** p<0.01, ** p<0.05, * p<0.1

Appendix 10 Potential Causality of the IR

If plot size was randomly distributed, or if change in plot size was a random treatment between 2003 and 2013, the inverse relationship estimated in plot panel data would be causal. Yet Table A24 illustrates that this is not the case. Column 1 regresses plot size on all covariates from Table 4 using ordinary least squares, and Columns 2 and 3 do the same using household-year-season fixed effects (as in Appendix 4) and plot fixed effects (as in Tables 3-7), respectively. In all three cases, it is clear that plot size is predicted by other covariates.

Column 4 of A24 explains change in plot size — the logarithm of the difference between plot size in 2013 and plot size in 2003 — as a function of 2003 covariates only, using household fixed effects. (For continuous covariates observed in both seasons of 2003 an average is used, and for binary covariates observed in both seasons of 2003 the maximum value is used.) Column 5 does the same, but additionally controls for starting plot size in 2003. This column suggests that conditional on starting plot size, plot size change is exogenous. (Results from Appendix 5 suggest the same.) However, we cannot condition on 2003 plot size in panel estimations of the IR, and so for our purposes, plot size cannot be viewed as exogenous.

We cannot, therefore, interpret the inverse relationship as causal. Yet, the results of Table 4 show the relationship to be remarkably robust to additional controls. The coefficient on plot size, which we interpret as the inverse relationship, is statistically indistinguishable across columns, and actually rises in magnitude between Column 1 (univariate regression) and Column 6 (full controls).

In order to explore the likelihood of causality we calculate Oster's bias-adjusted estimator γ^*, as defined in Equation 6. We do this five times, allowing X_{ijt} from Equation 5 to take the value of each set of controls in Columns 2-5 of Table 4, as well as the full set of controls in Column 6. We assume $\delta = 1$ and $R_{max} = 1.3R_5$, as suggested by Oster (2016).

These bounds are displayed in Table A25. None of them contain zero. The last set of bounds — drawn from Column 6 of Table 4, controlling for all covariates — suggest that the causal effect of plot size on plot productivity is virtually identical to the original, estimated effect. This is because controlling for these covariates increases R-squared while changing the estimated inverses relationship very little.

We can also alter the assumptions of $\delta = 1$ and $R_{max} = 1.3R_5$, to examine the range of bounds that are possible under various δ and R_{max} parameters. Figure A6 illustrates the bias-adjusted estimator γ^* calculated for every combination of $\delta \in [0, 2]$ and $R_{max} \in [0.5, 1]$, maintaining $\hat{\gamma_4} = -0.670$, $R_4 = 0.371$, $\hat{\gamma_5} = -0.667$, $R_5 = 0.433$, as in the final column of Table A25, i.e., based on the full set of controls in Table 4. Figure A6 illustrates that, if we consider the full set of time-varying plot controls as our observables, there is no feasible combination of δ and R_{max} parameters that suggests the causal inverse relationship to be lower than -0.6.

Table A24: Balance Test for Plot Size (OLS, Household-Time FE, Plot FE)

	(1) Plot Size	(2) Plot Size	(3) Plot Size	(4) Change in Size	(5) Change in Size
GPS-measured plot size '03 (log ha)					-0.502***
					(0.105)
Soil pH (pH)	1.900***	-0.113	-0.112	4.530**	3.977*
	(0.352)	(0.324)	(1.056)	(2.269)	(2.089)
Soil pH^2 (pH^2)	-0.149***	-0.00209	-0.000869	-0.349*	-0.320*
	(0.0295)	(0.0272)	(0.0872)	(0.191)	(0.173)
Soil sand (%)	0.00722***	-0.000908	0.0104***	0.00378	0.00834
	(0.00132)	(0.00182)	(0.00385)	(0.00628)	(0.00570)
Soil organic carbon (%)	-0.0468***	-0.0315**	-0.0733***	-0.00838	-0.00672
	(0.0105)	(0.0127)	(0.0280)	(0.0527)	(0.0489)
Labor intensity (log hrs/ha/day)	-0.401***	-0.447***	-0.254***	0.281***	0.0899
	(0.0154)	(0.0215)	(0.0444)	(0.0736)	(0.0825)
Organic amendment (binary)	0.281***	0.458***	0.273***	-0.397**	-0.0812
	(0.0594)	(0.0670)	(0.0886)	(0.178)	(0.174)
Inorganic fertilizer (binary)	-0.245	0.466***	-0.00592	0	0
	(0.273)	(0.163)	(0.526)	(.)	(.)
Irrigation (binary)	-0.214	0.143	-0.664***	-0.302	-0.105
	(0.170)	(0.128)	(0.241)	(0.221)	(0.371)
Terracing (binary)	0.0901*	0.289***	0.134	0.0226	0.137
	(0.0533)	(0.0644)	(0.109)	(0.262)	(0.243)
Head owns plot (binary)	-0.0244	-0.0275	0.138	0.0706	0.310
	(0.0514)	(0.116)	(0.120)	(0.423)	(0.464)
Head manages plot (binary)	0.0221	0.351***	0.157	-0.638	-0.468
	(0.0615)	(0.121)	(0.155)	(0.402)	(0.330)
(Head owns)X(Head manages)	-0.0405	-0.151	-0.292	0.448	-0.00681
	(0.0757)	(0.147)	(0.180)	(0.808)	(0.739)
Crops are rotated (%)	-0.0889**	0.142**	-0.211**	0.113	0.0845
	(0.0378)	(0.0575)	(0.0928)	(0.177)	(0.176)
Crops are mono-cropped (%)	0.0666	0.0123	0.380***	-0.0867	-0.148
	(0.0710)	(0.0840)	(0.141)	(0.254)	(0.210)
Mixed cropping (%)	0.273***	0.194**	0.466***	0.263	0.186
	(0.0722)	(0.0875)	(0.136)	(0.218)	(0.195)
Tubers grown (binary)	0.247***	0.212***	0.476***	-0.388**	-0.185
	(0.0343)	(0.0369)	(0.0984)	(0.182)	(0.170)
Cereals grown (binary)	0.351***	0.315***	0.208***	-0.446***	-0.253*
	(0.0337)	(0.0368)	(0.0710)	(0.144)	(0.131)
Legumes grown (binary)	0.244***	0.264***	0.177**	0.0145	0.0954
	(0.0357)	(0.0379)	(0.0737)	(0.170)	(0.167)
Bananas grown (binary)	-0.00194	0.00802	0.0676	-0.125	-0.144
	(0.0476)	(0.0569)	(0.113)	(0.206)	(0.195)
Cash crops grown (binary)	0.410***	0.230***	0.460***	-0.383**	-0.254
	(0.0466)	(0.0495)	(0.130)	(0.189)	(0.174)
Sample	Pooled	Pooled	Panel	Panel R1	Panel R1
Observations	4075	3476	1624	616	616
R^2	0.360	0.364	0.381	0.170	0.244

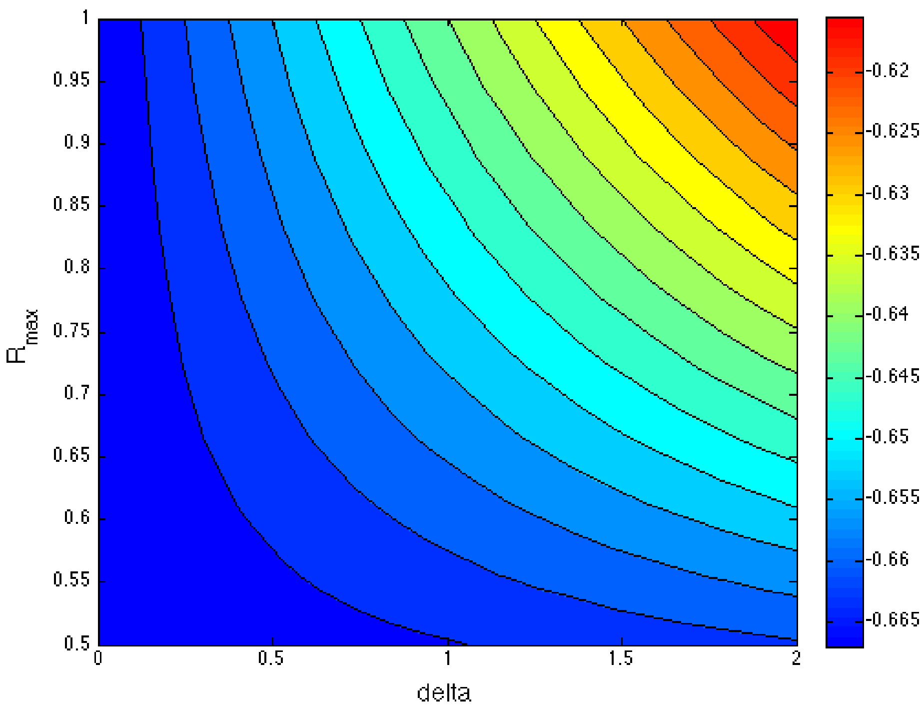
Dependent variable Cols 1-3: log(revenue/hectare)
Dependent variable Cols 4-5: log([2013 revenue/hectare] - [2003 revenue/hectare])
Column 1: Estimated with no fixed effects
Column 2: Estimated with household-year-season fixed effects
Columns 1, 2: Household-year-season-clustered standard errors in parentheses
Column 3: Estimated with plot fixed effects, plot-clustered standard errors in parentheses
Columns 4, 5: Estimated with household fixed effects, household-clustered standard errors in parentheses
Columns 4, 5: All covariates are from round 1 (R1), and the dependent variable
is change in plot size between 2003 and 2013
p<0.01, ** p<0.05, * p<0.1

Table A25: Bounds for Potential Causal Relationship t

	$R_{max} = 1.3 * R_5$, δ=1, $\hat{\gamma_4}$=-0.670, R_4=0.371				
	(1)	(2)	(3)	(4)	(5)
Column Controls	Soil	Inputs	Management	Crops	Full Set
R_5	0.380	0.393	0.393	0.393	0.433
Bounds $[\hat{\gamma_5}\ \gamma^*(R_{max}, \delta)]$	[-0.662, -0.561]	[-0.603, -0.244]	[-0.712, -0.937]	[-0.728, -1.039]	[-0.667, -0.661]

Coefficient $\hat{\gamma_4}$ and R_4 from Column 1 of Table 4
Coefficients $\hat{\gamma_5}$ and R_5 from Columns 2-6 of Table 4

Figure A6: Bias-Adjusted Estimator $\gamma^*(R_{max}, \delta)$
$(\hat{\gamma_4} = -0.670,\ R_4 = 0.371,\ \hat{\gamma_5} = -0.667,\ R_5 = 0.433)$



Appendix 11 More on the Edge Effect

Explaining Perimeter-Area Variation

Figure A7 illustrates a remarkably tight, linear, non-parametric relationship between plot size and perimeter-area ratio. It also displays kernel density distributions for both plot size and perimeter-area ratio. Neither distribution displays long tails on either side; medium-sized plots provide the bulk of variation both for plot size and perimeter-area ratio.

Because our primary results identify coefficients using plot fixed effects, Figure A8 displays the same non-parametric relationship and kernel density distributions, except for change in plot size over time, and change in perimeter-area ratio over time. Again, neither relationship displays a particularly long tail; the bulk of variation in both variables comes from the same, medium-change plots.

Table A26 examines the predictors of the perimeter-area ratio in our panel dataset via a regression framework. The first three columns are estimated via OLS, and so explain both cross-sectional variation and variation within plots over time. Columns 4-6 are estimated via plot fixed effects, and so explain only variation in perimeter-area ratio within plots over time. Column 1 shows that plots with interior vertices (that is, plots for which a corner cuts into the main area, perhaps tracing around an object) have higher perimeter area relationships, as we would expect. The perimeter-area ratio of a polygon theoretically decreases with number of sides — a triangle has the highest proportion of area around the periphery, and a circle the lowest. This appears in the data; in Column 1 we see that perimeter-area ratio is highest for triangular plots, and decreases at a diminishing rate with number of sides.

While Column 1 of Table A26 accounts for only plot shape, Column 2 of Table A26 accounts for only size. Shape variables explain 21 percent of variation in perimeter-area ratio, while plot size explains 88 percent of variation. This make it clear that plot size is the primary factor driving perimeter-area relationship. Yet plot shape variables still contribute to explanatory power in Column 3, even conditional on plot size. Roughly the same is seen under plot fixed effects, in Columns 4-6.

Causality of Edge Effect

Table A27 shows the edge effect to be robust to all controls previously considered — just as the inverse relationship was robust to these controls. The stability of the coefficient on perimeter-area ratio is again strongly suggestive of causality, and causal bounds can similarly be estimated along the lines suggested by Oster (2016).

As we did with the inverse relationship, we can calculate the univariate relationship between perimeter-area ratio and productivity, as in Equation 14. We can then add in controls X_{ijt}, as in Equation 15.

$$Y_{ijt} = \theta_4 \frac{P_{ijt}}{A_{ijt}} + \lambda_{ij} + \lambda_t + \varepsilon_{ijt} \tag{14}$$

$$Y_{ijt} = \theta_5 \frac{P_{ijt}}{A_{ijt}} + \beta X_{ijt} + \lambda_{ij} + \lambda_t + \varepsilon_{ijt} \tag{15}$$

Equation 14 is estimated in Column 1 of Table A27, and Equation 15 is estimated in Columns 2-6 of Table A27, allowing X_{ijt} to hold a different set of controls in each column. (These controls are identical to those considered in Table 5.)

We calculate the bias-adjusted perimeter-area coefficient θ^* as in Equation 16, where R_4 is the R-squared obtained by estimating the univariate relationship of Equation 14 (given in Column 1 of Table A27), and R_5 is the R-squared obtained by estimating the same relationship with controls as in Equation 15 (given in Columns 2-6 of Table A27).

$$\theta^*(R_{max}, \delta) = \hat{\theta}_5 - \delta \left[\hat{\theta}_4 - \hat{\theta}_5\right] \frac{R_{max} - R_5}{R_5 - R_4} \tag{16}$$

As done in Appendix 10 for the inverse relationship, we can then calculate bounding intervals for the coefficient on perimeter-area ratio, $\left[\hat{\theta}_5, \theta^*(min\{1.3R_5, 1\}, 1)\right]$, which follows Oster's suggested starting assumption of $\delta = 1$ and $R_{max} = 1.3R_5$.

These bounds are displayed in Table A28. They suggest that the causal parameter is somewhere around 1 or hovering above 1. Column 5 uses all controls to estimate the causal interval, and suggests that the causal perimeter lies within $[1.127, 0.975]$.

Additionally, using the full set of controls such that $\hat{\theta}_4 = 1.188$, $R_4 = 0.387$, $\hat{\theta}_5 = 1.127$, $R_5 = 0.440$, we calculate θ^* under the full possible range of R_{max} values and all plausible δ values. Figure A9 illustrates for almost all feasible combinations of δ and R_{max}, the bounding interval around a theoretically causal parameter will not contain zero. Only once $R_{max} > 9.44$ and $\delta > 1.68$ does the bounding interval contain zero.

Robustness of Edge Effect and the Role of Plot Shape

Tables A29 and A30 illustrate that the edge effect holds across crop subsets and ownership/management subsets, as does the inverse relationship. Additionally, it holds across plot size and perimeter-area ration quantiles, as illustrated by Table A31. (That is, like the inverse relationship, the effect is linear, rather than driven by extreme values of plot size or perimeter-area relationship.)

It is possible that the coefficient on perimeter-area ratio captures something about plot shape unrelated to peripheral productivity. It might be that plots with more perimeter per area (i.e., triangular plots, or 4-sided plots with acute angles) are more productive for reasons unrelated to the edge effect. If so, we would expect that controlling for plot shape directly, or for number of sides, would mitigate or eliminate the coefficient on perimeter-area ratio.

Columns 2 and 3 of Table A32 show that this is not the case — there is no direct, significant impact of shape on productivity, whether shape is quantified as number of plot sides (Column 2) or categorized into triangular, 4-sided, more than 4 sides (Column 3). The coefficient on perimeter-area ratio is unchanged between the base specification in Column 1, the specification controlling for plot sides in Column 2, and the within-plot-shape specification of Column 3. Figure A10 similarly illustrates that while productivity is, on average, highest for triangles and lowest for multi-sided plots, the difference is not significant.

However, Columns 4 and 5 of Table A32 demonstrate that the marginal impact of perimeter-area ratio does change with plot shape. For each additional plot side, the marginal impact of perimeter-area ratio decreases by 0.0762. For triangular plots, a ten percent increase in perimeter-area ratio results in a 14.4 percent increase in productivity; for plots with four sides this figure is 10.6 percent, and for plots with more than 4 sides (the omitted category) this figure is 7.9 percent. Figure A11, graphing productivity demeaned by year and season over perimeter-area ratio, illustrates that this differential can be seen in the (almost) raw data. Figure A12 again illustrates the differential by graphing productivity predicted by the regression model of Column 5, Table A32.

Investigating Multicollinearity

It is important to note that plot size and perimeter-area ratio are highly correlated, with a Pearson's Correlation Coefficient of -0.133. The log version of these coefficients is even more strongly correlated, with a correlation coefficient of -0.939. Essentially, perimeter-area ratio is a non-linear transform of plot size. It is logical, therefore, to be concerned that multicollinearity may in some way effect the coefficients estimated in Column 2 of Table 5, where both variables are included simultaneously as coefficients. We address this concern in a few ways.

First, Table A33 estimates the coefficient on perimeter-area ratio according to quintiles of correlation between plot size and perimeter-area relationship. (More specifically, log plot size is regressed on log perimeter-area ratio, and correlation quintiles are defined according to the residual.) The coefficient on perimeter-area ratio is stable across these quintiles.

Second, Table A34 displays a placebo test. We replace perimeter in the perimeter-area ratio with a new, placebo variable. This placebo variable has an identical distribution to perimeter but is randomly generated, and then divided by area in order to simulate a placebo version of the perimeter-area ratio. The logged versions of area and placebo-area ratio are highly correlated, with a correlation coefficient of -0.886 — close to the correlation of the true variables. Yet Table A34 illustrates that while placebo-area ratio has some explanatory power (Column 3), it is lower than the explanatory power of area alone (Column 1). This is in contrast to the true variable, which has higher explanatory power than area alone (Table 5). When both variables are controlled for simultaneously, the inverse relationship is unchanged. Again, this is in contrast to the results of Table 5, where the inverse relationship becomes zero once perimeter-area ratio is controlled for.

Third, Table A35 goes even further by replacing perimeter in perimeter-area ratio with a placebo variable that is not only identically distributed to perimeter, but is also similarly correlated with area. The logged versions of true perimeter and plot size are correlated with a coefficient of 0.934; the logged versions of this new placebo perimeter and plot size are correlated with a correlation coefficient of 0.932. Logged versions of placebo-area and plot size are correlated with a correlation coefficient of 0.939, just as with the true variables.

The results of this second placebo tests are identical to the first; the placebo-area variable has lower explanatory power than true area, and controlling for this variable in no way mitigates the inverse relationship. Together, Tables A33-A35 suggest that multicollinearity is unlikely to be driving the results in Table 5.

Alternate Indicators for Edge Effect

We hypothesize that perimeter-area ratio explains plot productivity because it is a proxy for the proportion of plot area that lies around the plot periphery. Essentially, the perimeter-area ratio specifies quantity perimeter per unit area. This suggests a less perfect proxy for the same concept — the number of plot sides per unit area. Number of sides and perimeter are highly related, with a correlation coefficient of 0.614. If quantity of perimeter per unit area drives up productivity, it would make sense for numbers of sides per unit area to also drive up productivity, and that controlling for this ratio would mitigate the inverse relationship.

This new ratio is actually more highly correlated with plot size than is perimeter-area ratio; while the logged version of plot size and perimeter-area ratio are correlated with a coefficient of -0.939, the logged versions of plot size and sides-area ratio are correlated with a coefficient of -0.952. (This is because there is less variation in number of sides than in perimeter.)

Table A36 estimates the same regressions as Table 5, but replacing perimeter with number of sides. Controlling for this ratio in Column 2 mitigates the inverse relationship, as we would expect if sides-area ratio is an imperfect proxy for proportion of plot area around the periphery. It does so less, however, than controlling for perimeter-area ratio. This makes sense, if perimeter-area ratio is a better proxy for the true variable of interest. (Additionally, it further suggests that multicollinearity does not drive the results in Table 5, since this new proxy is actually more collinear with plot size.) Column 3 shows that sides-area ratio does almost as well as plot size in explaining plot productivity — this was not true for the placebo tests in Tables A34 and A35.

An additional proxy can be found for the concept of perimeter, or perimeter-area ratio. We propose that any plot, “extra” or “unnecessary” perimeter can be quantified as the ratio between true perimeter and the perimeter that would be necessary for the same area, if the plot was a perfect square. While perimeter is correlated with area (r=0.85), the extra perimeter ratio is necessarily uncorrelated (r=0.04). We would expect extra perimeter to increase plot productivity, particularly when the extra perimeter is large with respect to plot area. Extra perimeter can therefore serve as a second, imperfect proxy for perimeter (one uncorrelated with area), and extra perimeter per hectare can serve as a proxy for perimeter-area ratio.

Table A37 estimates these regressions, similarly to Table A36. We see that indeed, the inverse relationship is mitigated again by half, and this time becomes insignificant once extra perimeter per hectare is controlled for. Column 3 implies that for every percentage increase in extra perimeter per hectare of plot, productivity increases by 0.6 percent.

Last, recall that we hypothesize that the inverse relationship exists largely because (across the entire sample) plot size is inversely correlated with perimeter-area ratio. And in fact, for about 90 percent of observations, if plot size goes up (down) between 2003 and 2013, perimeter-area ratio goes down (up). For a small selection of observations, however, perimeter-area ratio increases as plot size increases, or perimeter-area ratio decreases as plot size decreases. If the edge effect truly drives the inverse relationship, we would not expect to observe an inverse relationship for these observations. Rather, we would expect a positive relationship between plot size and productivity, as a decrease in perimeter-area ratio (and coincidentally in plot size) would drive a decrease in productivity, and an increase in perimeter-area ratio (and coincidentally in plot size) would drive a increase in productivity.

Table A38 tests this hypothesis. Column 1 estimates the inverse relationship for all observations for which plot size and perimeter-area ratio move in opposite directions over time. The estimated coefficient on plot size (-0.62) is almost identical to the estimated coefficient in full sample (-0.621). Column 2 displays results for the same regression, but for the sample of plots for which plot size and perimeter-area ratio move in the same direction. As hypothesized, for this sample of 234 plots there exists a positive relationship between plot size and productivity. Columns 3-5 run this same regression on random sub-samples of plots, in order to ensure that the result is not merely an artifact of reduced sample size. For all three columns, an inverse relationship is observed. (And while some sub-samples will result in a reduction of statistical significance or a reduction of coefficient magnitude, we have never observed a random sub-sample for which the estimated coefficient was positive.)

Magnitude of the Edge Effect

We estimate a large edge effect in our data, and it is logical to ask whether this effect, or the accompanying inverse relationship, can be simulated under reasonable assumptions. We walk through such a simulation in Figures A13 - A24.

Figures A13 and A14 illustrate the change in perimeter-area ratio that results from changes in plot shape (holding area constant) and changes in plot size (holding shape constant). Perimeter-area ratio increases as angles become more extreme (moving to the right in Figure A13) and decreases as size increases (moving to the right in Figure A14).

Figures A15 and A16 illustrate the accompanying changes in plot productivity (created as an area-weighted average of interior and peripheral productivity), given the simulated shape and size shifts. Peripheral area is taken to be 2 times interior productivity, a typically observed differential in controlled, agricultural trials, and the border area is taken to be a set length across all shapes (precisely, a tenth of the length of the squares's side). It is visually clear that productivity moves closely with perimeter area ratio — though not in an exactly linear fashion, given that perimeter-area ratio is merely a proxy for (peripheral area) / (total area).

Figures A17 and A18 illustrate the elasticity of productivity with respect to perimeter-area ratio, given the simulated shape and size shifts. These elasticities change across shapes, but for a peripheral-interior differential of 2, they hover between 0.2 and 0.27, meaning that a one percent increase in perimeter-area ratio — whether driven by changing shape or by changing size — increases productivity by around 0.2-0.27 percent. Notably, this elasticity is far less than edge effect parameter estimated in our results, which implied a one to one increase in productivity with perimeter-area ratio. Figures A19 and A20 again illustrate the elasticity of productivity with respect to perimeter-area ratio, but now assuming that peripheral area is 3.6 times interior productivity, as observe by Holman and Bednarz (2001). This assumption increases the elasticity considerably, now hovering between 0.37 and 0.46, though it still falls short of the one to one ratio observed in our estimations.

Why is the edge effect observed in our data so much greater than the simulated edge effect? We hazard that two factors likely play in. First, we are simulating a clear border region with differentially high productivity, and an interior region with homogenous productivity. Many papers instead note that productivity is higher around plot edges, and degrades slowly as one enters the plot (Holman and Bednarz, 2001). In such a case, there is not one peripheral area, but rather productivity is a degrading function of distance from plot edges. This would increase observed edge effect, though we do not simulate it as we have very little idea of what that function would look like.

Second, we are simulating productivity differentials observed in experimental agronomy trials — but such controlled trials will almost always observed a edge effect driven purely by biophysical factors. In farmer plots, where labor, input trends, harvesting intensity, etc., are not tightly controlled, behavioral mechanisms driven by farmer choices/behavior may increase the differential beyond that observed in controlled trials. This, too, would increase the edge effect.

Third, and even more speculatively, it is possible that plot shape drives productivity in some way that we do not understand. We take the association between perimeter-area ratio and productivity as strongly indicative of the edge effect. However, one might conservatively conclude that plot shape clearly plays into driving plot productivity, but that we do not fully understand why plot shape is so important.

Figures A21 - A24 illustrate the elasticity of productivity with respect to area. Figures A21 and A22 illustrate this elasticity while increasing plot size and holding shape constant. As with the edge effect, the inverse relationship observed is far lower than the inverse relationship estimated in our data. We simulate an inverse relationship of -0.07 to -0.17, while we estimate an inverse relationship of -0.6.

Figures A23 and A24 illustrate the same elasticity, but under simulated, simultaneous shifts in both plot shape and plot size. In Figure A23, the effect of the shape shifts dominates the effect of the size shifts, and perimeter-area ratio rises. Hence, productivity increases, and so we do not observe the inverse relationship. In Figure A24, the effect of the size shifts dominate the effect of the shape shifts, and perimeter-area ratio decreases. Hence, productivity decreases, and we observe an inverse relationship. This simulates the effect we found empirically in Table A38: for plots where size increases while perimeter-area ratio also increases, or plots where size decreases while perimeter-area ratio also decreases, we do not expect to find an inverse relationship. Instead, we expect to estimate a positive relationship between plot size and productivity for these plots.

Figure A7: Plot Size vs. Perimeter-Area Ratio

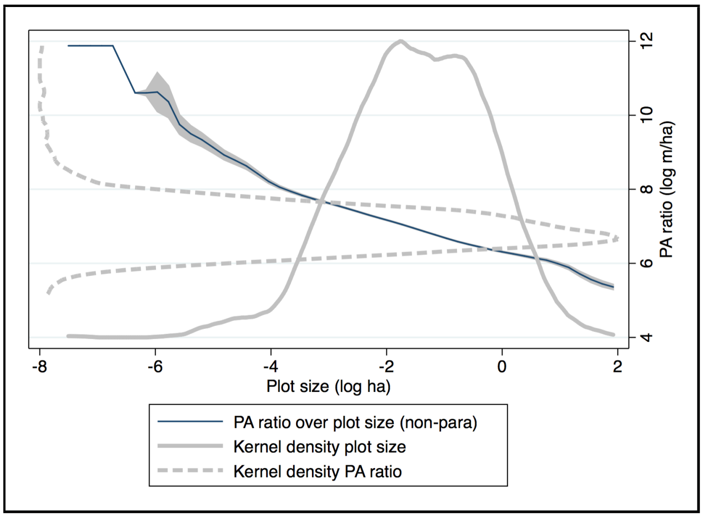


Figure A8: Plot Size vs. Perimeter-Area Ratio: Change between 2003 and 2013

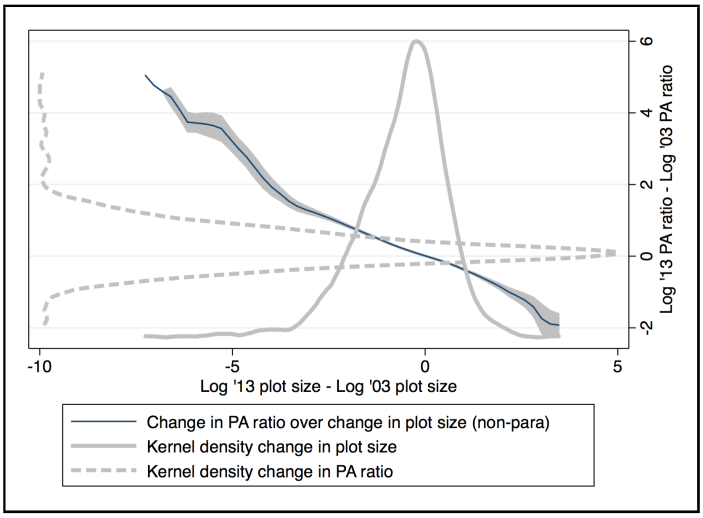


Table A26: Perimeter-Area Ratio Explained by Shape and Size (Plot Panel)

	OLS			Plot Fixed Effects		
	(1) P-A Ratio	(2) P-A Ratio	(3) P-A Ratio	(4) P-A Ratio	(5) P-A Ratio	(6) P-A Ratio
Plot has inner vertices (binary)	0.191***		0.0530***	0.0264		0.0589***
	(0.0457)		(0.0156)	(0.0456)		(0.0160)
Plot has 3 sides (binary)	1.103***		0.403***	1.060***		0.301***
	(0.238)		(0.101)	(0.277)		(0.0782)
Plot has 4 sides (binary)	0.0246		0.0146	0.181**		0.00739
	(0.0593)		(0.0173)	(0.0719)		(0.0223)
Number of sides (#)	-0.211***		-0.00771	-0.0329		0.0142
	(0.0272)		(0.0109)	(0.0444)		(0.0165)
(Number of sides)^2	0.00702***		0.00200***	-0.000909		0.000725
	(0.00110)		(0.000499)	(0.00224)		(0.000843)
GPS-measured plot size (log ha)		-0.511***	-0.529***		-0.530***	-0.576***
		(0.0103)	(0.00865)		(0.0169)	(0.0149)
Observations	2170	2182	2170	2170	2182	2170
Adjusted R^2	0.206	0.883	0.907	0.244	0.881	0.910

Dependent variable: log(perimeter/hectare)
Cols 4-6: Estimated via OLS
Cols 4-6: Estimated with plot fixed effects
Plot-clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A27: Robustness of Edge Effect (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity	(4) Plot Productivity	(5) Plot Productivity	(6) Plot Productivity
Perimeter-area ratio (log m/ha)	1.188***	1.174***	1.081***	1.229***	1.238***	1.127***
	(0.140)	(0.145)	(0.137)	(0.131)	(0.132)	(0.126)
Soils	No	Yes	No	No	No	Yes
Inputs	No	No	Yes	No	No	Yes
Management	No	No	No	Yes	No	Yes
Crops	No	No	No	No	Yes	Yes
Observations	1623	1623	1623	1623	1623	1623
Adjusted R^2	0.386	0.393	0.404	0.401	0.399	0.432
R^2	0.387	0.396	0.407	0.405	0.402	0.440

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 10 with various controls
*** p<0.01, ** p<0.05, * p<0.1

Table A28: Bounds for Potential Causal Relationship

	$R_{max} = 1.3 * R_5$, δ=1, $\hat{\theta}_4$=1.188, R_4=0.387				
	(1)	(2)	(3)	(4)	(5)
Column Controls	Soil	Inputs	Management	Crops	Full Set
R_5	0.396	0.407	0.405	0.402	0.440
Bounds $\left[\hat{\theta}_5 \ \theta^*(R_{max}, \delta)\right]$	[1.174, 0.989]	[1.081, 0.428]	[1.229, 1.506]	[1.238, 1.640]	[1.127, 0.975]

Coefficient $\hat{\theta}_4$ and R_4 from Column 1 of Table A27
Coefficients $\hat{\theta}_5$ and R_5 from Columns 2-6 of Table A27

Figure A9: Bias-Adjusted Estimator $\theta^*(R_{max}, \delta)$
$(\hat{\theta}_4 = 1.188,\ R_4 = 0.387,\ \hat{\theta}_5 = 1.127,\ R_5 = 0.440)$

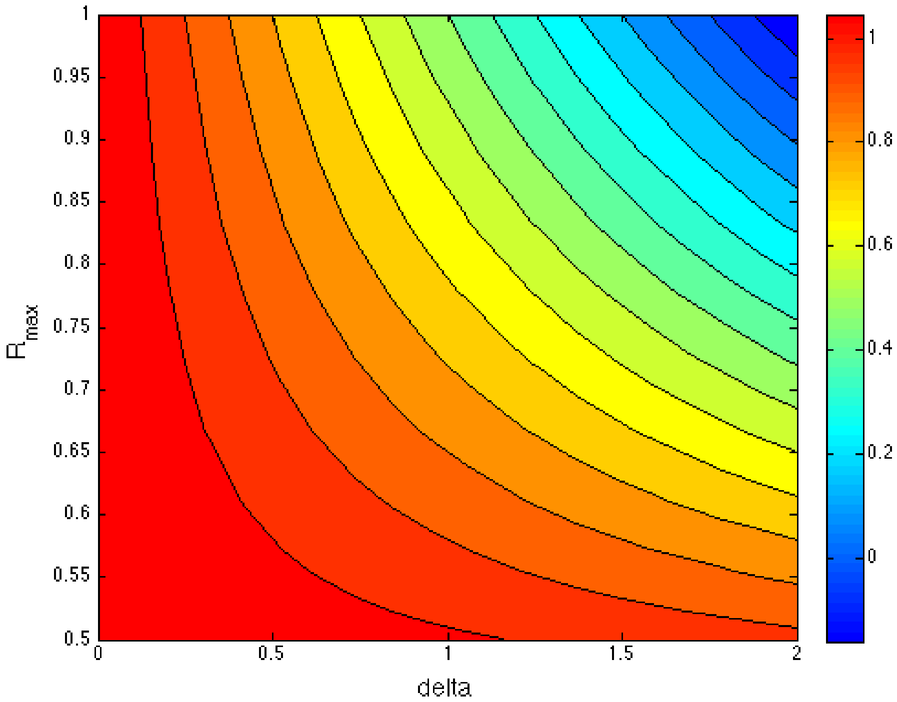


Table A29: The Edge Effect by Crop (Plot Panel)

	(1) Plot Productivity (All Plots)	(2) Plot Productivity (Tubers)	(3) Plot Productivity (Cereal)	(4) Plot Productivity (Legumes)	(5) Plot Productivity (Banana)	(6) Plot Productivity (Cash Crops)
Perimeter-area ratio (log m/ha)	1.099***	1.190***	1.484***	0.887***	0.732***	1.063***
	(0.0961)	(0.193)	(0.123)	(0.163)	(0.138)	(0.326)
Observations	2181	744	1015	1071	831	544
Adjusted R^2	0.392	0.303	0.480	0.340	0.278	0.306

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 10 for data subsets by crop
p<0.01, ** p<0.05, * p<0.1

Table A30: The Edge Effect by Ownership/Management (Plot Panel)

	(1) Plot Productivity (Head Owns)	(2) Plot Productivity (Head Manages)	(3) Plot Productivity (Owns & Manages)	(4) Plot Productivity (Crops Rotated)	(5) Plot Productivity (Mono-Cropped)	(6) Plot Productivity (Mixed Cropping)
Perimeter-area ratio (log m/ha)	1.197***	0.881***	1.034***	1.435***	1.038***	1.330***
	(0.142)	(0.133)	(0.144)	(0.285)	(0.206)	(0.132)
Observations	1551	1298	1154	610	872	1162
Adjusted R^2	0.411	0.325	0.339	0.281	0.351	0.466

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 10 for data subsets by ownership/management
p<0.01, ** p<0.05, * p<0.1

Table A31: Edge Effect by Quantiles (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity
Perimeter-area ratio (log m/ha)	1.099***		
	(0.0961)		
P-A ratio quantiles=1 × Perimeter-area ratio (log m/ha)		1.364***	
		(0.192)	
P-A ratio quantiles=2 × Perimeter-area ratio (log m/ha)		1.342***	
		(0.180)	
P-A ratio quantiles=3 × Perimeter-area ratio (log m/ha)		1.273***	
		(0.171)	
P-A ratio quantiles=4 × Perimeter-area ratio (log m/ha)		1.275***	
		(0.163)	
P-A ratio quantiles=5 × Perimeter-area ratio (log m/ha)		1.287***	
		(0.150)	
Plot size quantiles=1 × Perimeter-area ratio (log m/ha)			1.116***
			(0.150)
Plot size quantiles=2 × Perimeter-area ratio (log m/ha)			1.096***
			(0.161)
Plot size quantiles=3 × Perimeter-area ratio (log m/ha)			1.063***
			(0.169)
Plot size quantiles=4 × Perimeter-area ratio (log m/ha)			1.113***
			(0.176)
Plot size quantiles=5 × Perimeter-area ratio (log m/ha)			1.122***
			(0.186)
Observations	2181	2181	2181
Adjusted R^2	0.392	0.402	0.398

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Table estimates Equation 10 for data subsets
*** p<0.01, ** p<0.05, * p<0.1

Table A32: Edge Effect by Plot Shape (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity	(4) Plot Productivity	(5) Plot Productivity
Perimeter-area ratio (log m/ha)	1.099***	1.112***	1.107***	1.463***	0.785***
	(0.0961)	(0.100)	(0.0956)	(0.162)	(0.121)
Number of sides (#)		0.00837		0.526***	
		(0.0148)		(0.175)	
Plot has 3 sides (binary)			0.0341		-7.674***
			(0.298)		(1.909)
Plot has 4 sides (binary)			-0.115		-2.302**
			(0.0928)		(0.961)
(Perimeter-area ratio)x(Number of sides)				-0.0785***	
				(0.0265)	
(Perimeter-area ratio)x(Plot has 3 sides)					0.982***
					(0.242)
(Perimeter-area ratio)x(Plot has 4 sides)					0.319**
					(0.138)
Observations	2181	2169	2181	2169	2181
Adjusted R^2	0.392	0.396	0.393	0.401	0.404

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
p<0.01, ** p<0.05, * p<0.1

Figure A10: Productivity by Shape

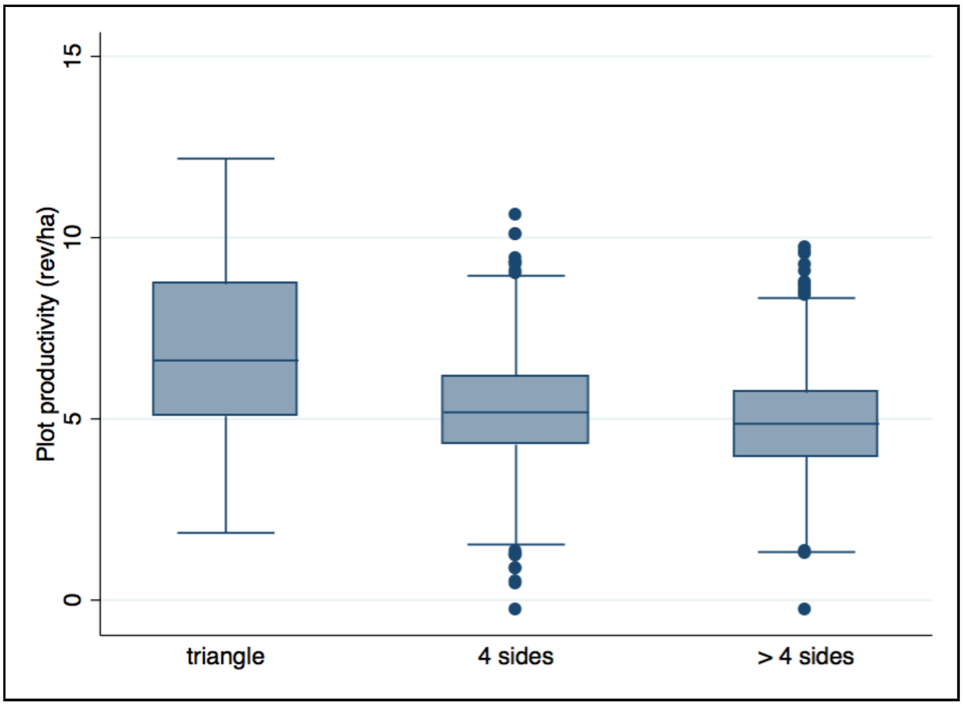


Figure A11: Productivity Demeaned by Round and Season

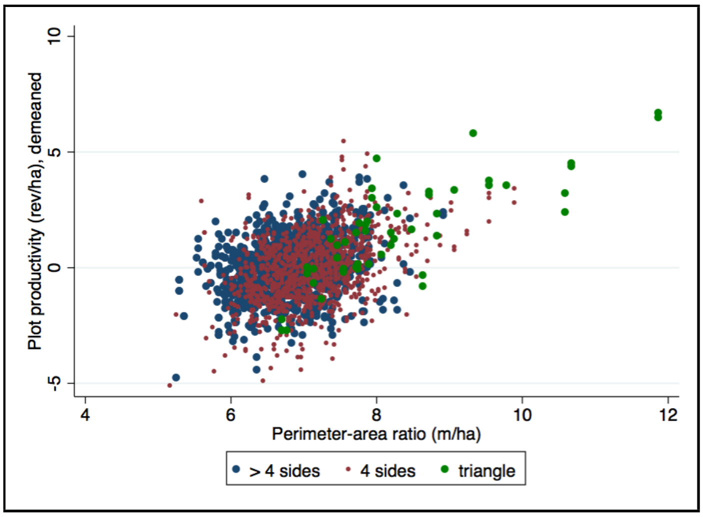


Figure A12: Productivity Prediction from Table A32 Col 5

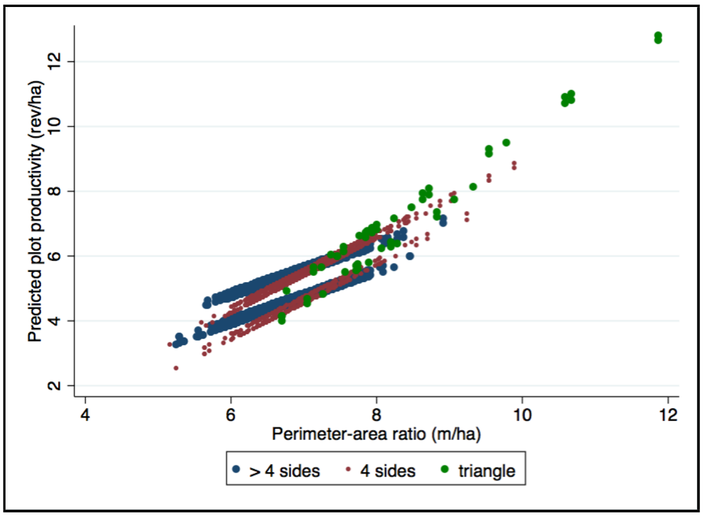


Table A33: Edge Effect by Area Correlation with Perimeter-Area Ratio (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity
GPS-measured plot size (log ha)	-0.0664	
	(0.136)	
Correlated Q1 × Perimeter-area ratio (log m/ha)	1.007***	1.115***
	(0.253)	(0.0973)
Correlated Q2 × Perimeter-area ratio (log m/ha)	1.049***	1.156***
	(0.254)	(0.0979)
Correlated Q3 × Perimeter-area ratio (log m/ha)	1.033***	1.141***
	(0.254)	(0.0984)
Correlated Q4 × Perimeter-area ratio (log m/ha)	1.027***	1.135***
	(0.252)	(0.0975)
Correlated Q5 × Perimeter-area ratio (log m/ha)	1.008***	1.113***
	(0.246)	(0.0952)
Observations	2181	2181
Adjusted R^2	0.396	0.396

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
p<0.01, ** p<0.05, * p<0.1

Table A34: Edge Effect Placebo Test (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity	(4) Plot Productivity
GPS-measured plot size (log ha)	-0.621***	-0.589***		-0.622***
	(0.0636)	(0.0741)		(0.0637)
Placebo-area ratio (log m/ha)		0.0332	0.370***	
		(0.0412)	(0.0495)	
Placebo (log m)				0.0332
				(0.0412)
Observations	2181	2181	2181	2181
Adjusted R^2	0.381	0.381	0.332	0.381

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
p<0.01, ** p<0.05, * p<0.1

Table A35: Edge Effect Placebo Test with Multicollinearity (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity	(4) Plot Productivity
GPS-measured plot size (log ha)	-0.621***	-0.708***		-0.535***
	(0.0636)	(0.0818)		(0.0910)
Placebo-area ratio (log m/ha)		-0.173	0.853***	
		(0.117)	(0.116)	
Placebo (log m)				-0.173
				(0.117)
Observations	2181	2181	2181	2181
Adjusted R^2	0.381	0.382	0.339	0.382

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
p<0.01, ** p<0.05, * p<0.1

Table A36: Suggestive Edge Effect: Number of Sides (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity	(4) Plot Productivity
GPS-measured plot size (log ha)	-0.621***	-0.365***		-0.674***
	(0.0636)	(0.110)		(0.0694)
Sides-area ratio (log #/ha)		0.309**	0.682***	
		(0.125)	(0.0714)	
Sides (log #)				0.309**
				(0.125)
Observations	2181	2169	2169	2169
Adjusted R^2	0.381	0.387	0.380	0.387

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
p<0.01, ** p<0.05, * p<0.1

Table A37: Suggestive Edge Effect: Extra Perimeter (Plot Panel)

	(1) Plot Productivity	(2) Plot Productivity	(3) Plot Productivity	(4) Plot Productivity
GPS-measured plot size (log ha)	-0.621***	0.327		-0.529***
	(0.0636)	(0.235)		(0.0498)
Extra perimeter† / area (log ratio/ha)		0.903***	0.604***	
		(0.231)	(0.0554)	
Extra perimeter† (ratio)				0.176***
				(0.0297)
Observations	2181	2181	2181	2181
Adjusted R^2	0.381	0.393	0.392	0.401

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
†Extra perimeter = (true perimeter) / (perimeter if square)
p<0.01, ** p<0.05, * p<0.1

Table A38: Inverse Relationship Relies on PA Ratio (Plot Panel)

	(1) Plot Productivity (Same Direction)	(2) Plot Productivity (Opposite Directions)	(3) Plot Productivity (Random Sample)	(4) Plot Productivity (Random Sample)	(5) Plot Productivity (Random Sample)
GPS-measured plot size (log ha)	-0.620***	0.433	-0.542***	-0.527***	-0.551***
	(0.0647)	(0.269)	(0.174)	(0.151)	(0.0894)
Observations	1947	234	218	220	216
Adjusted R^2	0.399	0.138	0.392	0.307	0.416

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
p<0.01, ** p<0.05, * p<0.1

Figure A13: Perimeter-area Ratio Changing Shape

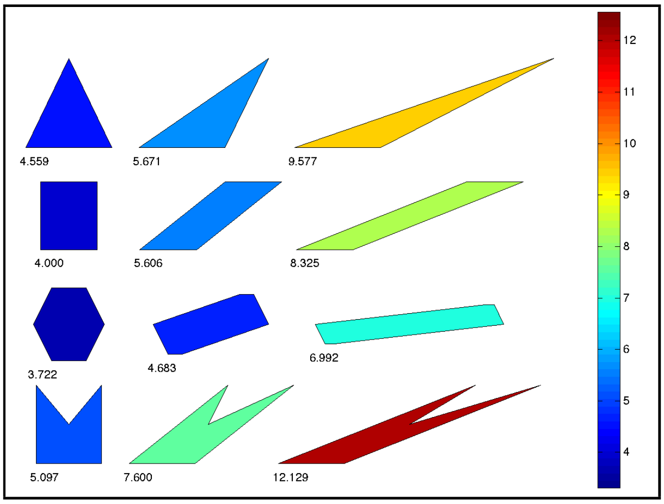


Figure A14: Perimeter-area Ratio Changing Size

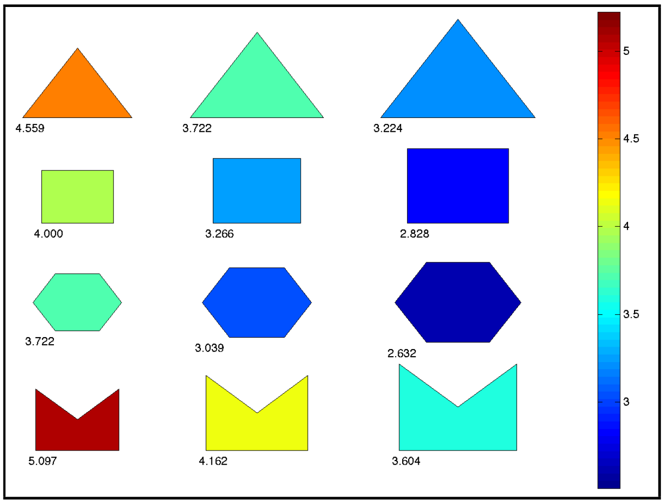


Figure A15: Productivity ($Y^P = 2Y^I$) Changing Shape

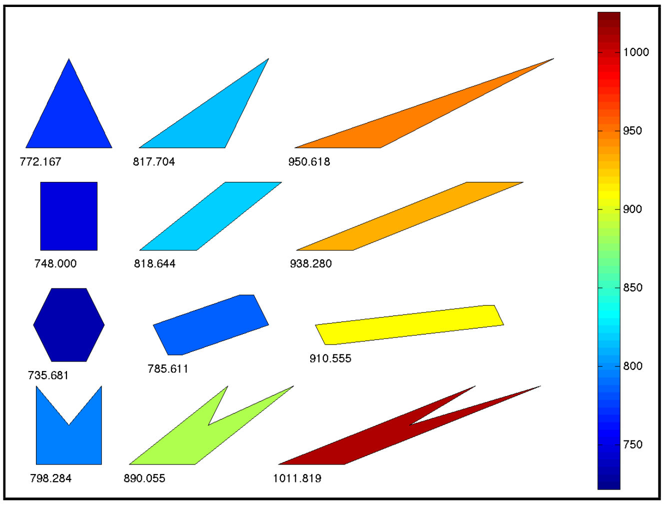


Figure A16: Productivity ($Y^P = 2Y^I$) Changing Size

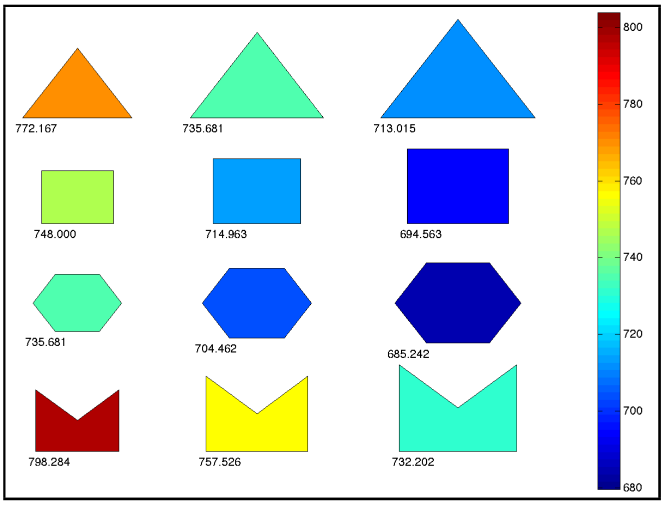


Figure A17: Elasticity wrt PA ratio ($Y^P = 2Y^I$): Changing Shape

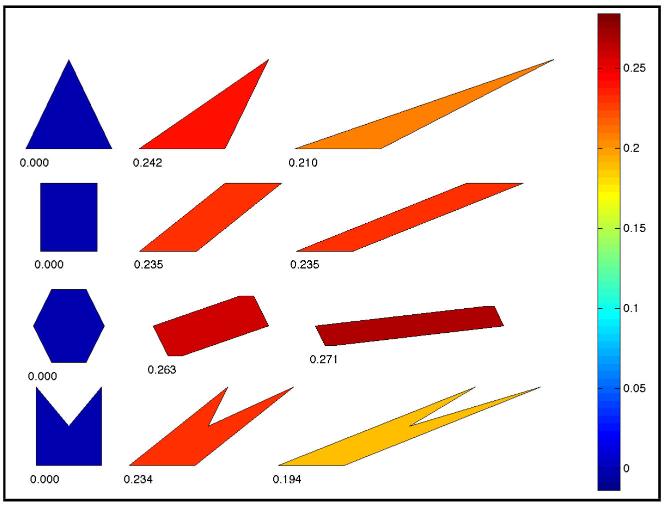


Figure A18: Elasticity wrt PA ratio ($Y^P = 2Y^I$): Changing Size

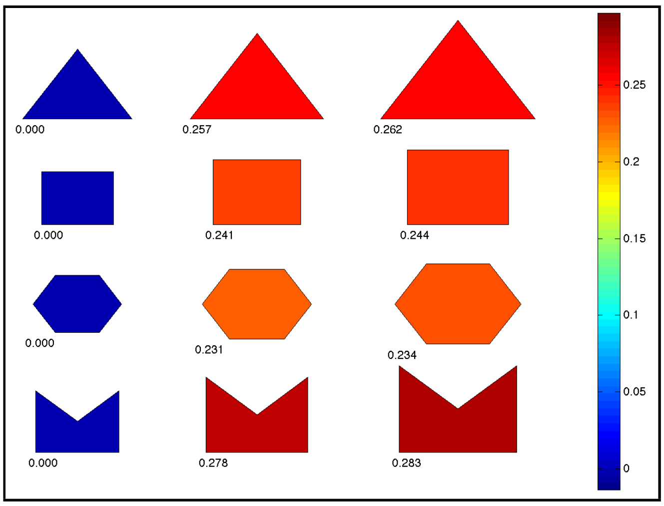


Figure A19: Elasticity wrt PA ratio ($Y^P = 3.6Y^I$): Changing Shape

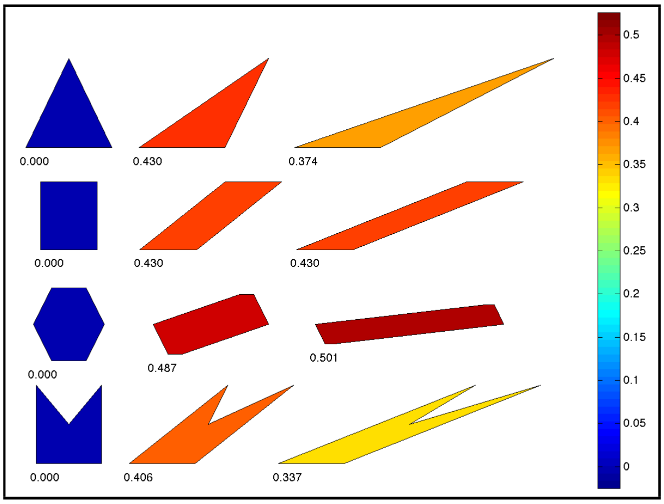


Figure A20: Elasticity wrt PA ratio ($Y^P = 3.6Y^I$): Changing Size

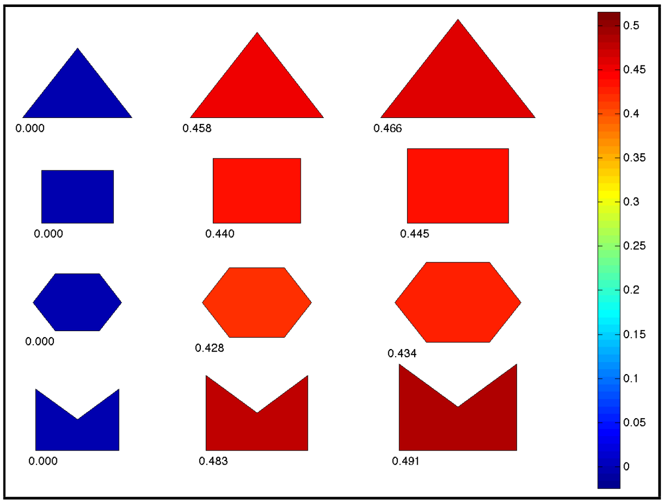


Figure A21: Elasticity wrt Area ($Y^P = 2Y^I$): Changing Size

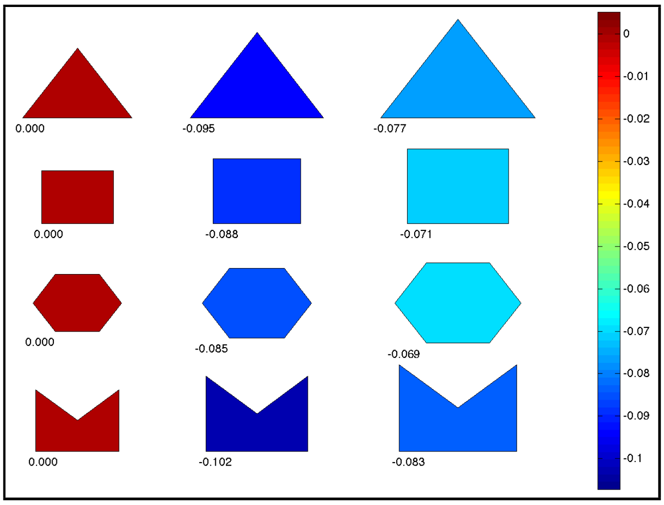


Figure A22: Elasticity wrt Area ($Y^P = 3.6Y^I$): Changing Size

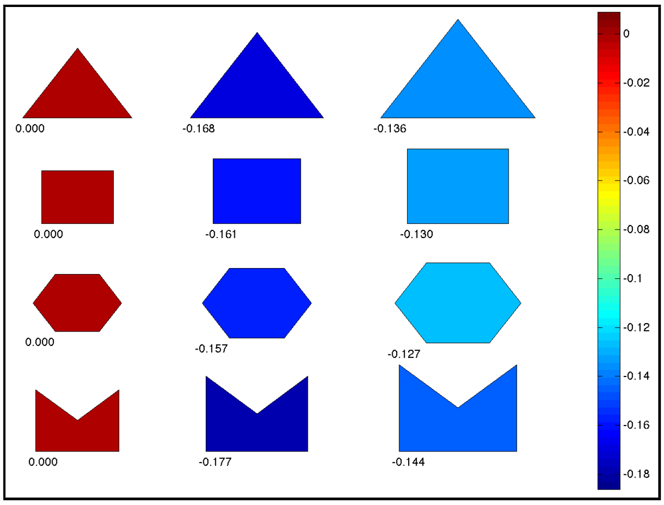


Figure A23: Elasticity wrt Area ($Y^P = 2Y^I$): Changing Shape and Size

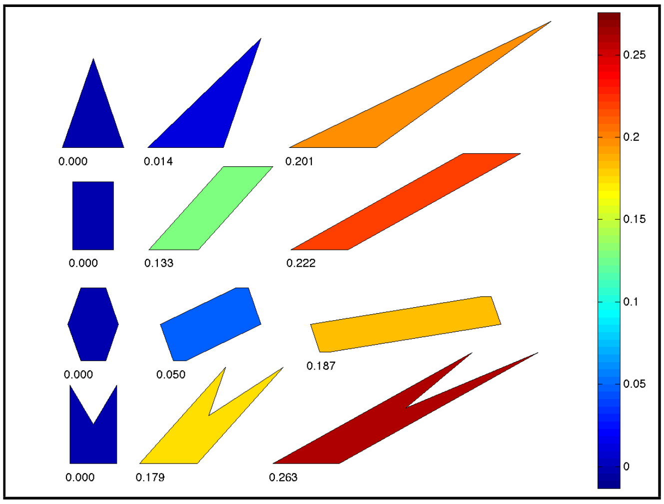
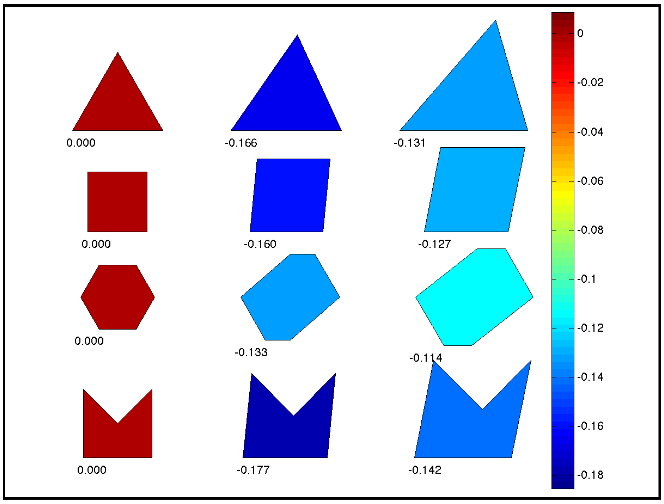


Figure A24: Elasticity wrt Area ($Y^P = 3.6Y^I$): Changing Shape and Size



Appendix 12 Exogeneity of Perception Error

When pooling data across plots and rounds, Figures A2 and A3 illustrate a clear, non-parametric relationship between perception error, plot size and the perimeter-area ratio. Over-estimation is negatively correlated with plot area and positively correlated with the perimeter-area ratio. Under-estimation moves in the opposite direction, though with a slightly noisier relationship. (Far more plots are over-estimated than under-estimated, and so the noise around under-estimation may be due to small sample size.) In both cases, perception error is measured in absolute terms, as a percent of the GSP-measured plot area.

Figure A25: Plot Size Perception Error over Plot Size

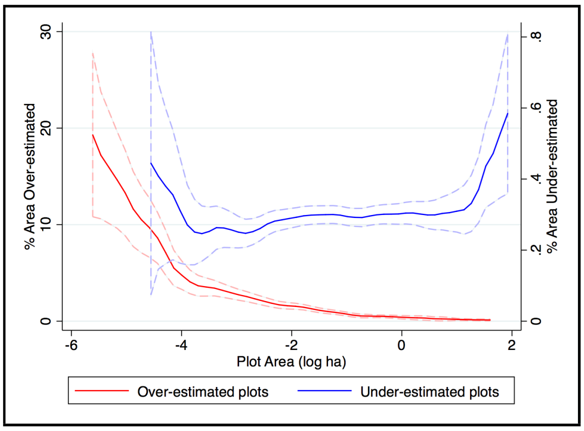
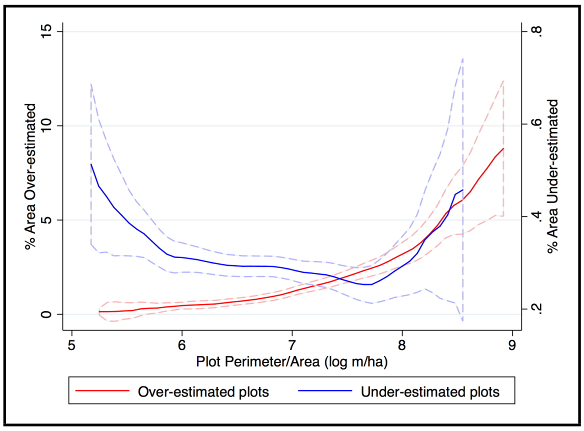


Figure A26: Plot Size Perception Error over Perimeter-Area Ratio



However, Column 1 of Table A39 shows that under plot fixed effects, neither plot area nor the perimeter-area ratio predict the over-estimation of plot size. (The same is true if plot area and the perimeter-area ratio are controlled for in a linear fashion. We choose quadratic controls due to the shape of the relationships in Figures 1 and 2.) Columns 2-5 control for other plot conditions — the same covariates that were considered as potential omitted variables in Table 4. The majority of these variables are also unrelated to over-estimation; only a few coefficients are significant, no more than one might expect by chance.

Column 1 of Table A40 similarly models the under-estimation of plot size as a quadratic function of plot area and the perimeter-area ratio, under a plot fixed effect model. In this case, it does appear that the perimeter-area ratio is weakly, negatively related to under-estimation. Yet conditional on plot area and the perimeter-area ratio, most other variables are unrelated to over-estimation. Only irrigation and tubers grown are significantly related, but only 6 observations are used to pick up irrigation variation under the plot fixed effect model, making this a volatile coefficient.

Last, Table A41 models the binary indicator for over-estimation of plot size, using the same covariates again. As with Tables A39 and A40, this binary variables appears unrelated to plot conditions under the fixed effect model, once conditioned on plot area and plot perimeter-area ratio.

By and large, it appears likely that perception error, under the fixed effect model, is exogenous to plot conditions, perhaps with the exception of crop choice.

Table A39: Exogeneity of Continuous Over-Estimation (Plot Panel)

	(1) Over-Estimation	(2) Over-Estimation	(3) Over-Estimation	(4) Over-Estimation	(5) Over-Estimation
GPS-measured plot size (log ha)	0.417	0.632	0.315	-0.0211	0.116
	(0.631)	(0.638)	(0.654)	(0.790)	(0.795)
(GPS-measured plot size)^2	0.198	0.186	0.172	0.177	0.199
	(0.242)	(0.276)	(0.271)	(0.330)	(0.233)
Perimeter-area ratio (log m/ha)	-15.37	-15.53	-16.76	-17.78	-14.11
	(12.80)	(12.12)	(13.22)	(14.65)	(12.35)
(Perimeter-area ratio)^2	1.219	1.224	1.285	1.330	1.113
	(0.903)	(0.863)	(0.946)	(1.042)	(0.857)
Soil pH (pH)		7.621*			
		(4.430)			
Soil pH^2 (pH^2)		-0.631*			
		(0.378)			
Soil sand (%)		0.00816			
		(0.0214)			
Soil organic carbon (%)		0.216			
		(0.216)			
Labor intensity (log hrs/ha/day)			0.122		
			(0.137)		
Organic amendment (binary)			0.409		
			(0.529)		
Inorganic fertilizer (binary)			0.544		
			(1.161)		
Irrigation (binary)			-0.140		
			(0.548)		
Terracing (binary)			0.646		
			(0.503)		
Head owns plot (binary)				0.0128	
				(0.897)	
Head manages plot (binary)				-1.166	
				(1.190)	
(Head owns)X(Head manages)				0.642	
				(1.310)	
Crops are rotated (binary)				-0.140	
				(0.310)	
Crops are mono-cropped (binary)				-1.236	
				(0.917)	
Mixed cropping (binary)				-0.563	
				(0.803)	
Tubers grown (binary)					0.0409
					(0.454)
Cereals grown (binary)					0.206
					(0.431)
Legumes grown (binary)					1.060**
					(0.451)
Bananas grown (binary)					1.044**
					(0.407)
Cash crops grown (binary)					0.705
					(0.497)
Observations	860	758	816	758	860
Adjusted R^2	0.325	0.351	0.325	0.333	0.344

Estimated with plot and year fixed effects; Plot-clustered standard errors in parentheses
Observations include plots that were over-estimated; 1 observation per year
p<0.01, ** p<0.05, * p<0.1

Table A40: Exogeneity of Continuous Under-Estimation (Plot Panel)

	(1) Under- Estimation	(2) Under- Estimation	(3) Under- Estimation	(4) Under- Estimation	(5) Under- Estimation
GPS-measured plot size (log ha)	-0.143 (0.0873)	-0.173 (0.131)	-0.150 (0.110)	-0.156 (0.108)	-0.130 (0.0866)
(GPS-measured plot size)^2	-0.0335 (0.0382)	-0.0776* (0.0431)	-0.0520 (0.0440)	-0.0222 (0.0385)	-0.0463 (0.0442)
Perimeter-area ratio (log m/ha)	-3.783** (1.682)	-4.331** (1.924)	-4.569** (2.132)	-3.258* (1.703)	-3.948** (1.768)
(Perimeter-area ratio)^2	0.262** (0.130)	0.310** (0.145)	0.318* (0.163)	0.212 (0.129)	0.275** (0.137)
Soil pH (pH)		1.242** (0.520)			
Soil pH^2 (pH^2)		-0.113** (0.0446)			
Soil sand (%)		-0.00180 (0.00292)			
Soil organic carbon (%)		-0.0138 (0.0228)			
Labor intensity (log hrs/ha/day)			0.00214 (0.0224)		
Organic amendment (binary)			0.0822 (0.0910)		
Inorganic fertilizer (binary)			0.148 (0.101)		
Irrigation (binary)			-0.344* (0.180)		
Terracing (binary)			0.0608 (0.0649)		
Head owns plot (binary)				0.145** (0.0689)	
Head manages plot (binary)				0.164 (0.105)	
(Head owns)X(Head manages)				-0.131 (0.127)	
Crops are rotated (binary)				0.0105 (0.0504)	
Crops are mono-cropped (binary)				-0.00590 (0.0731)	
Mixed cropping (binary)				0.0175 (0.0684)	
Tubers grown (binary)					-0.0757 (0.0473)
Cereals grown (binary)					-0.0534 (0.0442)
Legumes grown (binary)					-0.0613 (0.0438)
Bananas grown (binary)					0.0871 (0.0771)
Cash crops grown (binary)					-0.121* (0.0735)
Observations	612	509	582	555	612
Adjusted R^2	0.107	0.163	0.172	0.186	0.164

Estimated with plot and year fixed effects; Plot-clustered standard errors in parentheses
Observations include plots that were under-estimated; 1 observation per year
p<0.01, ** p<0.05, * p<0.1

Table A41: Exogeneity of Binary Over-Estimation (Plot Panel)

	(1) Over-Est Binary	(2) Over-Est Binary	(3) Over-Est Binary	(4) Over-Est Binary	(5) Over-Est Binary
GPS-measured plot size (log ha)	-0.0227	0.0164	0.0177	-0.0396	-0.0606
	(0.0695)	(0.0847)	(0.0799)	(0.0894)	(0.0743)
(GPS-measured plot size)^2	0.0312**	0.0295	0.0404**	0.0273	0.0270*
	(0.0158)	(0.0185)	(0.0176)	(0.0204)	(0.0161)
Perimeter-area ratio (log m/ha)	1.079***	1.391***	1.519***	1.149**	0.986**
	(0.402)	(0.460)	(0.453)	(0.510)	(0.414)
(Perimeter-area ratio)^2	-0.0666***	-0.0807***	-0.0919***	-0.0705**	-0.0618**
	(0.0257)	(0.0289)	(0.0292)	(0.0329)	(0.0263)
Soil pH (pH)		-0.242			
		(0.463)			
Soil pH^2 (pH^2)		0.0200			
		(0.0379)			
Soil sand (%)		-0.00249			
		(0.00205)			
Soil organic carbon (%)		0.00618			
		(0.0138)			
Labor intensity (log hrs/ha/day)			-0.0377**		
			(0.0153)		
Organic amendment (binary)			-0.0405		
			(0.0524)		
Inorganic fertilizer (binary)			-0.0276		
			(0.146)		
Irrigation (binary)			0.000518		
			(0.216)		
Terracing (binary)			0.0828*		
			(0.0492)		
Head owns plot (binary)				-0.0261	
				(0.0615)	
Head manages plot (binary)				-0.134*	
				(0.0811)	
(Head owns)X(Head manages)				0.148	
				(0.0948)	
Crops are rotated (binary)				0.0229	
				(0.0419)	
Crops are mono-cropped (binary)				-0.0185	
				(0.0615)	
Mixed cropping (binary)				0.0112	
				(0.0616)	
Tubers grown (binary)					-0.0203
					(0.0402)
Cereals grown (binary)					0.00921
					(0.0397)
Legumes grown (binary)					0.0780**
					(0.0363)
Bananas grown (binary)					-0.0361
					(0.0556)
Cash crops grown (binary)					0.114**
					(0.0561)
Observations	1476	1271	1401	1316	1476
Adjusted R^2	0.165	0.152	0.180	0.167	0.172

Estimated with plot and year fixed effects; Plot-clustered standard errors in parentheses
Observations include all plots; 1 observation per year
p<0.01, ** p<0.05, * p<0.1

Appendix 13 More on Perception Error

Tables A42 and A43 indicate that the productivity impacts of plot size misperception are qualitatively unchanged across crop and ownership/management categories, though significance is lost on many coefficients. Over-estimation of plot size is associated with higher productivity (with diminishing returns) for all crops, and under-estimation of plot size is associated with lower productivity (with diminishing returns) for all crops but banana. Over-estimation of plot size is associated with higher productivity (with diminishing returns) for plots under all categories of ownership and management, though the effect of under-estimation is lost.

Additionally, Table A44 shows that labor intensity increases with over-estimation of plot size, significantly with diminishing returns, just as productivity does. The effect of under-estimation is lost, perhaps because there is far less variation in under-estimation than in over-estimation, making these coefficients difficult to estimate if the effect is weak.

Table A42: The Effects of Farmer Misperception of Plot Size by Crop (Plot Panel)

	(1) Plot Productivity (Tubers)	(2) Plot Productivity (Cereal)	(3) Plot Productivity (Legumes)	(4) Plot Productivity (Banana)	(5) Plot Productivity (Cash Crops)
Farmer over-estimates plot (binary)	-0.736**	-0.251	-0.313	-0.200	-0.202
	(0.331)	(0.207)	(0.228)	(0.286)	(0.329)
Over-estimate (% area)	0.0549	-0.00297	0.127*	0.220***	0.133
	(0.107)	(0.0729)	(0.0739)	(0.0554)	(0.0811)
Over-estimate squared	0.00000489	-0.000686	-0.00361	-0.00629***	-0.00346
	(0.00352)	(0.00258)	(0.00235)	(0.00222)	(0.00261)
Under-estimate (% area)	-7.762***	-2.222*	-3.752***	2.009	-1.013
	(2.329)	(1.216)	(1.424)	(1.718)	(2.187)
Under-estimate squared	11.69***	2.130	4.699***	-1.449	1.852
	(3.374)	(1.382)	(1.799)	(1.981)	(2.841)
Observations	744	1015	1071	831	544
Adjusted R^2	0.340	0.503	0.387	0.330	0.359

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Plot area and area-perimeter ratio are controlled for quadratically in all columns
Table estimates Equation 12 for data subsets
p<0.01, ** p<0.05, * p<0.1

Table A43: The Effects of Farmer Misperception of Plot Size by Ownership/Management (Plot Panel)

	(1) Plot Productivity (Head Owns)	(2) Plot Productivity (Head Manages)	(3) Plot Productivity (Owns & Manages)	(4) Plot Productivity (Crops Rotated)	(5) Plot Productivity (Mono-Cropped)	(6) Plot Productivity (Mixed Cropping)
Farmer over-estimates plot (binary)	-0.0731	0.199	0.360	-1.175*	-0.524	0.0632
	(0.194)	(0.208)	(0.243)	(0.631)	(0.326)	(0.219)
Over-estimate (% area)	0.139***	0.115*	0.0624	0.198*	0.198***	0.202***
	(0.0518)	(0.0625)	(0.0711)	(0.102)	(0.0748)	(0.0504)
Over-estimate squared	-0.00542*	-0.00310	-0.000551	-0.00717	-0.00722**	-0.00620***
	(0.00287)	(0.00243)	(0.00300)	(0.00465)	(0.00318)	(0.00181)
Under-estimate (% area)	0.327	0.631	1.750	-6.727*	-1.568	0.405
	(0.997)	(1.181)	(1.357)	(3.537)	(2.215)	(1.488)
Under-estimate squared	0.0251	-0.722	-1.969	8.185*	1.303	-0.281
	(1.158)	(1.443)	(1.614)	(4.273)	(3.097)	(2.011)
Observations	1551	1298	1154	610	872	1162
Adjusted R^2	0.433	0.354	0.361	0.306	0.393	0.512

Dependent variable: log(revenue/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Plot area and area-perimeter ratio are controlled for quadratically in all columns
Table estimates Equation 12 for data subsets
p<0.01, ** p<0.05, * p<0.1

Table A44: Labor Intensity Effects of Farmer Misperception of Plot Size (Plot Panel)

	(1) Labor Intensity	(2) Labor Intensity	(3) Labor Intensity
Farmer over-estimates plot (binary)	-0.308*	-0.304*	0.00615
	(0.168)	(0.168)	(0.201)
Over-estimate (% area)	0.0763*	0.0870**	0.0701
	(0.0404)	(0.0417)	(0.0477)
Over-estimate squared	-0.00144	-0.00205	-0.000877
	(0.00149)	(0.00154)	(0.00160)
Under-estimate (% area)	-0.0234	-0.0301	1.951*
	(1.015)	(1.029)	(1.179)
Under-estimate squared	-0.421	-0.444	-3.217**
	(1.294)	(1.324)	(1.446)
Plot Area, P-A Ratio	Yes	Yes	Yes
$(\text{Area})^2$, $(\text{P-A Ratio})^2$	No	Yes	Yes
Additional Plot Controls	No	No	Yes
Observations	2076	2076	1624
Adjusted R^2	0.209	0.212	0.256

Dependent variable: log(hours/hectare)
Estimated with plot, year and season fixed effects
Plot-clustered standard errors in parentheses
Additional plot controls are from Column 6 of Table 3, excluding labor intensity
Table estimates Equation 12 for labor intensity, rather than for productivity
*** p<0.01, ** p<0.05, * p<0.1