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Does land fragmentation reduce efficiency: Micro evidence from India

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The arguments favoring fewer land fragments on a farmer-by-farmer basis are many and includes reduced travel times, less boundary waste, feasibility of larger-scale productive investment, and ease supervision of labor to name a few. Thus, it is not surprising to find some of the earlier empirical research a priori assuming land fragmentation as an indicator of productive inefficiency (Bardhan 1973). On the other hand, opponents of land consolidation programs note the benefits of fragmented land holdings to reduce risk and encouraging more diversified production. In India, an additional problem associated with land consolidation programs from a distributional aspect is that such programs tend to benefit those with larger land holdings more than those with smaller holdings since the implicit costs of land fragmentation are higher for larger farms (Mearns 1999). It has been suggested that fragmented land holdings allow producers to be more adaptive to certain circumstances but may more non-adaptive when factor prices and technology changes (McClosky 1975). In the end, the issue of whether or not land fragmentation negatively affects agricultural productivity is an empirical one.

To quantify the degree of land fragmentation a variety of different methods and indicators have been proposed and includes include number of plots, distances to plots, and an index capturing dissimilarities across farmed plots of land (i.e. Simpsons Index). From the perspective of an individual farmer or household, we can think of fragmentation as touching on spatial dispersion, number of fragments, and dissimilarity in fragments or a combination of these. In this paper we consider each of these dimensions in more detail and argue that much of the related research considers only one or two of these dimensions or does not adequately distinguish among them making effective targeting of policy difficult. For example, Simpson's index, an oft used measure to quantify the degree of land fragmentation, combines variation in areas among fragments with the number of fragments at the household level making it impossible to distinguish between these two dimensions.

A major contribution of this study is to consider these three conceptually distinct dimensions of land fragmentation separately and to examine how they impact agricultural productivity. In particular we use the Rural Economic Development Survey (REDS) and estimate a Cobb-Douglas production function to determine the effect fragmentation has on productivity. By breaking down fragmentation into these three dimensions we are better able to disentangle and asses the importance of the different aspects commonly associated to fragmentation. Our results indicate the number of fragments dimension has a significantly negative impact on productivity. Furthermore, the two other dimensions spatial disconnect and variability in area, do not significantly impact productivity having controlled for the number of fragments.

The next section recounts the related literature and is followed by a discussion of different fragmentation measures including a decomposition of Simpson's index. The next section presents a framework to test the impact of different fragmentation measures on fragmentation and is followed by a description of the REDS data used for estimation. We then present and discuss the results of our analysis and round out the paper with a discussion of the implications of our findings.

Literature Review

One of the earlier studies on the impact of land fragmentation and productivity, by Blarel et al. (1992) use a range of plot and household-level characteristics including plot area, total area farmed, and distance to household in combination with Simpson's index and the number of fragments to examine land fragmentation's impact on yields using producer survey data in Ghana and Rwanda. Blarel et al. (1992) note that Simpson's index is sensitive to the number of fragments and is one reason why they consider each of these measures of fragmentation separately. However, since Simpsons index combines both variation in number of fragments as well as number of fragments, it is difficult to distinguish between these two dimensions of fragmentation. Estimating the impact on yields via an exponential, log-log functional form, Blarel et al. (1992) do not find that fragmentation has a significant impact on productivity. Interestingly, distance from home to plot was found to have a positive impact on yields in some sub-samples of their data. Another early study considering land fragmentation's impact on productivity is Nguyen, Cheng and Findlay (1996). They use average plot size as a proxy for land fragmentation and estimate a Cobb-Douglas production function argue consolidation resulting in larger plot size would result in higher yields based on their finding yields for maize, wheat, and rice in China are increasing in plot size. Noting that Simpson's index combines the number of plots and the variation in sizes, Tan, Heerink, Kruseman, and Qu (2008) conclude that fragmentation does not significantly impact production costs of rice farmers in China although they do find that distance between the home and plot do significantly increase production costs.

Wu, Liu, and Davis (2005) using a 1995 sample of households in China estimate an average production function and do not find fragmentation has a statistically significant impact on productivity. However, a subsequent study by Chen, Huffman, and Rozelle (2006) propose that land fragmentation impacts technical efficiency and not the average production frontier prompting them to estimate a stochastic production function using prefecture-level data where they find land fragmentation, as measured by number of plots and Simpson's Index, does result in inefficiency. Using provincial-level data, Carter and Estrin (2001) use cultivated land per capita to capture fragmentation and, implementing a stochastic frontier approach, and finds fragmentation negatively impacts technical efficiency.

Using number of plots, average plot size, and a measure of the distribution of land fragmentation called the Januszewski index, Jha, Nagarajan, and Prasanna (2005) use a household panel dataset for which plot-level data on size as well as crops grown was collected for two villages in Southern India and use this to examine the impact of fragmentation on both yield as well as efficiency. Using a translog production function and considering two crop production sequences, Samba-Blackgram and Samba-Cotton, they find that land fragmentation as measured by the number of plots has a negative impact average yields. They use this finding as grounds to test for a relationship between fragmentation on technical efficiency and subsequently find evidence that such a relationship does exist by way of a stochastic production function.

Using number of plots as a measure of land fragmentations to determine the impact on technical efficiency, Wan and Chen (2001) find that loss due to fragmentation ranges from slightly less than 4 percent for maize to approximately 15 and 17 percent for late rice and wheat respectively. Wan and

Cheng (2001) further suggest that elimination of land fragmentation could increase output of food grains by as much as 15 percent in China. Fleisher and Liu (1992) reported a potential gain in the order of 8 percent. However, Wan and Cheng (2001) also note that while the gains from land consolidation are significant, economies of scale are too small in which the policy focus should be directed towards consolidation rather than increasing land holdings.

To date the literature generally suggests that land fragmentation is detrimental to productivity although the existing research has yet to produce empirical evidence that adequately captures land fragmentation in its many dimensions. Still, land fragmentation is often totted as undesirable and policy has been enacted to reduce the degree of land fragmentation where this is perceived to be a problem. Such a program includes the 1988 comprehensive agricultural development (CAD) program in China which included provisions for land consolidation but was not successful in doing so (Wu, Liu, and Davis 2005).

In India, consolidation programs have been implemented to reduce the degree of land fragmentation, an issue which has garnered greater importance due to, among other factors, divisions in property resulting from inheritance. Verma and Bromley (1987) refer to land fragmentation as a "serious problem" and note the inconvenience associated with fragmentation, particularly from the point of view of the larger producers. Land reform legislation in India started to get underway on a state-by-state basis starting mid 19th century, continuing into the 1980's. In some instances where institutional design have been conducive to success, such as in Uttar Pradesh, land consolidation programs have reportedly led to reduced dependency for many farmers, and have increased the economic viability of many farms (Oldenburg 1990). Through a variety of early land reform and consolidation programs, in India around a third of the total cultivated area in India was reported to have been consolidated by the mid-1980s, with the majority of this in Punjab, Haryana, Uttar Pradesh, Maharashtra and Madhya Pradesh (Thangaraj 1995) and largely due to state programs (Mearns 1999). Mearns (1999) suggests the legacy of mahalwari tenure systems may have made the task of land consolidation easier in Punjab and Haryana while in other states (Tamil Nadu, Kerala) some consolidation has been achieved through land market activity where legislative provisions for land consolidation are not a factor.

Measures of Land Fragmentation

Land fragmentation is said to exist when a household (HH) operates on more than one separate piece of land. For the purposes of our study, a land fragment is defined as a contiguous piece of land on which the HH engages in production. In this section we review some common measures used to quantify land fragmentation (number of fragments, Simpson's Index), present some results highlighting the limitations of the often used Simpson Index, and describe some alternative fragmentation measures

Let f=1,…,F to index a particular land fragment which is engaged by the household for agricultural production. One simple fragmentation measure, the number of fragments, (F), has been used by to test whether productivity is affected by number of fragments (Blarel et al. 1992, Van Hung, MacAulay, and Marsh 2007). Having a highly fragmented land portfolio requires farmers to devote additional resources to transporting themselves and their equipment to other plots and diverts resources away from what would otherwise be productively applied to production. However, producers with multiple fragments may benefit since can operate on land of differing quality allowing them to diversify their crops and reduce production and price risks.

The Simpson index has been used by a number of authors to quantify the effect of land fragmentation on agricultural productivity (Blarel et al. 1992; Tan, Heerink, Kruseman, and Qu CER 2008; and others). Letting a_f be the area of fragment *f* for a particular household, Simpson's index[1] is defined as:

$$1 - \left[\frac{\sum_f a_f^2}{\left(\sum_f a_f\right)^2}\right]$$

A farmer whose land fragments are of varying sizes (in terms of area) would have a high measure of fragmentation according to the Simpson index. For the Simpsons index, a value of zero means that the HH farms a single, contiguous land fragment and that all farmed land is completely consolidated.

As noted by Blarel et al. (1992), Simpson's index combines variation in fragment area along with number of fragments and it is not possible to distinguish between these dimensions. Since number of plots and dissimilarity in size are two different factors, ideally these two should be separated out when attempting to pinpoint the precise impact land fragmentation has on productivity. In particular, Simpson's index is necessarily increasing in the number of fragments, and is decreasing in the variability in size among fragments. To see this, note that Simpson's index can be re-written as follows

$$= 1 - \left[\frac{\sum_f a_f^2}{(F\bar{a})^2}\right]$$

Where $\bar{a} = \frac{1}{F}\sum a_f$. Note that since $\sigma^2 = \frac{\sum_f\left(a_f - \bar{a}\right)^2}{F}$ using the formula for population variance, we can also show $\sigma^2 = \frac{1}{F}\sum_f\left(a_f^2 - 2a_f\bar{a} + \bar{a}^2\right) = \frac{1}{F}\left[\sum_f a_f^2 - F\bar{a}^2\right]$. Rearranging we can show that $\sum_f a_f^2 = F\sigma^2 + F\bar{a}^2$=$F(\sigma^2 + \bar{a}^2)$. This can be substituted into the numerator of the equation for Simpsons index as follows

$$S = 1 - \left[\frac{n(\sigma^2 + \bar{a}^2)}{(F\bar{a})^2}\right]$$

$$\rightarrow S = 1 - \frac{(\sigma^2 + \bar{a}^2)}{F\bar{a}^2}$$

It then follows that Simpsons index is increasing in the number of land fragments, $\frac{\partial S}{\partial F} = \frac{(\sigma^2 + \bar{a}^2)}{(F\bar{a})^2} > 0$, but decreasing in the variability of fragment area, $\frac{\partial S}{\partial \sigma^2} = \frac{-1}{(F\bar{a})^2} < 0$. From this little exercise it is clear that Simpsons index does capture two aspects of land fragmentation, number of and variability in area of

[1] Another fragmentation index that can also be shown to confound the effects of number of fragments and variability in areas is the Januszewski index $K = \frac{\left(\sum a_f\right)^{1/2}}{\sum a_f^{1/2}} = \frac{(n\bar{a})^{1/2}}{\sum a_f^{1/2}}$ (used in Jha, Nagarajan, Prasanna 2005).

fragments, but these tend to move in different directions. An increase in the number of fragments is generally considered to represent more fragmentation and would tend to increase the value of the Simpson index, while an increase in variation among land fragment areas, generally thought of as increased fragmentation, actually reduces the value of this index. Thus in empirical applications it is easy to see how the effects of fragmentation may be confused when using Simpsons index as it combines two fragmentation dimensions and, what is more, tends to move the index in different directions depending on whether or fragmentation is increased in the number or dissimilarity dimensions.

To help distinguish between the effect of number of fragments and variability in fragment area we proposal a modified dissimilarity index which is "purged" of the influence of number of fragments. That is, a modified measure index which captures variability in fragment area relative to the average fragment size and is not confounded by number of fragments. In particular, the measure of fragment variability we propose is $S^{+} = \frac{\left[(a_f - \bar{a})^2\right]^{1/2}}{\bar{a}}$. This measures how variable, in area terms, a particular fragment is relative to the average fragment area. With possible values from 0 and upwards, it is clear S^{+} is increasing in variability of areas but does not depend on the number of fragments. A value of 0 indicates that all fragments are of the same area (in the trivial case with only one fragment the value of this index is also zero).

A third aspect of fragmentation, we wish to consider is distance and the role it plays on agricultural productivity. In the literature distances from the fragment to the home have been used in a number of applications (i.e. Blarel et al. 1992). However, measuring the distance between a particular fragment and home alone does not adequately capture how spatially "disconnected" a particular fragment is from the rest of the farming operation. If we consider, for example, a HH which is actively engaged in production on two distinct land fragments, a suitable metric for the role of distance would ideally include how far a particular fragment is from the home *as well as* the distance to the other fragment. If the average distance between the HH and each fragment happens to be 900metres, then we might expect distance to be more of a limiting factor if each fragment is on opposite sides of the HH in which case the distance between fragments is 1.8km. However, if the fragments are actually quite close together, then costs associated with moving factors of production (equipment and labor) between fragments is much reduced as would any associated monitoring costs. Letting dh_f be the distance (in meters) from a fragment to the home location, and d_{fk} be the distance between a particular fragment *f* and *k*, one measure of effective distance (*e-dist*) is expressed as:

$$edist = \frac{dh_f + \sum_{k \neq f} d_{fk}}{F}$$

Prior household surveys have collected information on distances (physical, or time) from the fragment to the home location but we are unaware of any surveys that would have collected the information needed to compute a measure of effective distance as described above. Fortunately, one of the unique characteristics of the REDS survey is that comprehensive distance information that includes distances between each fragment and home *and* distances to other HH fragments is collected. This allows us to compute measures that capture fragmentation along the spatial dimension that could not be empirically measured in prior applications.

Capturing the Effect of Fragmentation on Productivity

Many household's produce on one or more fragments and may even produce multiple crops on a single, contiguous fragment. As a result, formulating our model and organizing the data is most realistic from a multi-output perspective. The value of output (*y*) is thus aggregated to form a single measure since inputs are reported only at the fragment level and do not necessarily differentiate between field crops where two or more crops are produced on the same fragment in a given season. Inputs (x_i's) include the usual suspects such as seed, fertilizer, machinery, labor, and land, the specifics of which are discussed in greater detail in the next section describing the data.

In choosing among alternative production functions the Cobb-Douglas is an appealing choice here since we are primarily interested in how land fragmentation impacts production in general rather than fragmentation-input interactions. In addition, since we are allowing a variety of field crops to feed into the value of output from each land fragment we are invariably going to be faced with the problem of zero-value inputs for some factors of production which causes obvious problems when estimating a function in log-log format. We circumvent this problem by introducing a dummy variable for inputs whose value is equal to one when an input is missing and replacing the non-defined log of the input with zero. Letting the z_i's be the relevant land fragmentation variables, which may include nonlinear trans the production function takes the following form:

(Equation 1)

$$\ln y = \sum \beta_i \ln x_i^* + \sum \delta_i \, d_i + \sum \gamma_j z_j + \varepsilon$$
$$where\ x_i^* = \begin{cases} x_i\ if\ x_i > 0 \\ 1\ if\ x_i = 0 \end{cases} and\ \ d_i = \begin{cases} 0\ if\ x_i > 0 \\ 1\ if\ x_i = 0 \end{cases}$$

Using this framework we can evaluate how each of the fragmentation variables impacts production individually as well as in combination. In particular, given a cleaner measure of variability in fragment areas, estimating the above production including a measure of area variability, spatial separation/distances, and number of fragments, we can consider how each of these each of fragmentation factors into productivity in general. Whether or not one dimension of fragmentation is relatively more important, or if these dimensions are jointly significant are empirical questions that can be addressed in this framework with the appropriate data.

To allow for non-linearities in the way in which land fragmentation can enter the production function the *z's* can include quadratic terms. Thus, when determining the marginal impacts of say number of fragments on output, for example, the elasticity will include coefficient estimates associated with the level as well as quadratic term for the number of fragments, the numerical value of which is evaluated at a particular point, often the mean. For example, in the model $lny = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_a ln(F) + \beta_b [ln(F)]^2$, the elasticity of output with respect to number of fragments evaluated at the mean is computed as

$$\varepsilon_F|_{\bar{F}} = \frac{\partial y}{\partial F} * \frac{\bar{y}}{\bar{F}} = \beta_a + 2\beta_b \overline{ln(F)}$$

where overbars indicate mean values.

Data

To compute the comprehensive set of land fragmentation indices discussed above we use the Rural Economic and Demography Survey (REDS) covering rural households in India for the period 2005-6. Excluding perennial crops like sugar cane and after removing outlier observations and otherwise cleaning the survey data we are left with nearly fragment-production 15,000 observations from approximately 4,400 households. A nationally representative sample, these households were drawn from 227 villages across 17 states. In all, the dataset we are working with here represent production information from nearly 9,000 individual fragments.

Country-wide, the average number of land fragments averages 3.2 and ranges from just under 1.3 in Gujarat to nearly 5 in Bihar State (Table 1). The number of fragments indicates the extent to which farmers' land use occurs on different, non-contiguous plots of land. The number of fragments represents *defacto* land use activity actually taking place on the ground whereas the number of subdivisions represents the degree to which lands are fragmented in an administrative or legal sense. With an average number of subdivisions per fragment of 1.87, in relative terms there is greater variation across the sample in numbers of sub divisions per fragment than number of fragments per farmer (coefficient of variation equals (1.68/1.87) vs. (2.04/3.17). It is evident from Table 1 the extent to which multiple subdivisions are farmed together as a single fragment depends to a certain extent on the state in question. Farmers in the northern States of Haryana and Punjab appear more likely to operate fragments comprised of a number of subdivisions, while states such as Andhra Pradesh, Karnataka, Kerala, and Tamil Nadu tend to have farmers combining fewer subdivisions per fragment.

A unique feature of the REDS is the level of detail and the amount of information collected regarding the spatial distribution of land used for production. For each household, information was collected on every land fragment and includes not only the area and distance to the home, but also the distance to all other fragments. Using the distance from a particular fragment to every other land fragment that is under the control of the household allows us to compute a measure of that varies by fragment showing how spatially "near" each fragment is relative to other fragments under production allowing us to compute the distance measure described earlier (*edist*). We find the average distance between a particular fragment and other fragments and the household is 800 meters (Table 2). We also find the average value of Simpson's Index to be 0.47, the average number of fragments equals 3.1, and a value of 0.36 for the dissimilarity in area variable.

Estimating a production function in terms of value of output allows us to incorporate a wider variety of crops so long as inputs are also reported in value terms so we can consistently compare values of marginal product across different crops. The summary statistics from for the sample data are presented in Table 2. The variable to be explained in our regression analysis, value of agricultural product per fragment, has average roughly 18,600 Rs. or approximately 10,300 Rs. /acre.

For inputs there are a number of instances where values are not reported explicitly as would be expected when some of these inputs are provided by the household themselves or obtained from neighbors in which case the exchange may not involve money. When part of all of a particular input is reported as physical quantity, rather than monetary value, the value of input is imputed using a representative per-unit input cost. Since our analysis covers a range of crops we combine similar inputs to make the number of inputs overall more manageable are represent these in value terms. For example, seed input was combined with seedlings under a single heading. In some instances for rice, the number of seedlings was reported and this is converted into kg's and multiplied by the price per unit as determined from local (i.e. village) data. If sufficient price data were not available locally, we use state-level averages. The average seed input cost was slightly more than 6 percent with an average cost of roughly 1,100 Rs. per fragment.

Fertilizer input combines chemical/synthetic and organic fertilizer under a single heading. Since organic fertilizer (manure) may be provided by the family, an imputed (shadow) value is obtained by multiplying the quantity input by the price where the price is determined as above with priority for using price obtained from local, then state, and finally national averages. Where input values for pesticides and fungicides were not available, the value of this input is imputed using per-unit input prices for the same crop where these prices were gather from local, then state, then national averages. The average fertilizer cost is 1,200 Rs./acre representing 11 percent of total production cost. While the average cost to pesticides and fungicides is just under 400 Rs the use of this input varies considerably across the sample as indicated by the large standard deviation.

Reported in number of bullock days, animal power includes both hired and family provided and averages 240 Rs. The value of bullock input is computed by combining hired and family supplied bullocks and multiplying this by the rental rate for bullocks from the village survey. To capture mechanization and mechanical input we use the total of hired and owned implement days and multiply this by the rental rate per implement day using first household-level data, and successively filling missing values using village, then state, and then national averages for implement rental rates for similar crops. Irrigation combines the cost associated with open and bore well (excluding labor), user charges for government canal and other public sources, and other purchased irrigation. When these costs for each of these categories were not reported but positive days for one or more of these types of irrigation were reported, the input value for this category was imputed in a similar manner as described above except matching with similar crops was not imposed.

When computing labor input the types of activities include land preparation, sowing, weeding, fertilizer application, pest control, irrigation, harvesting, and supervision. The REDS breaks down both hired and family labor by activity for each of men, women, and children. The wage rates applied to men, women, and children are based on information collected from village surveys conducted as part of the REDS. In the village survey, wages are reported for different activities for each of men, women, and children and allow us to determine a wage bill for each activity and then aggregate across all activities to obtain the cost of hired labor. Labor input is further separated according to family and hired labor. When computing the implicit cost of family labor an opportunity cost of labor equal the village wage rate for the same type and activity is used. Where the wage rate for a particular agricultural activity was not reported for a particular village, the wage rate for the same activity in a neighboring village was used.

As a share of total cost, land is the single most important factor of production followed with family labor a distant second. When imputing land cost a separate rate is used for each of land under irrigation and non-irrigated land as these two generally differ. Where applicable, rental rates were converted into seasonal equivalents (from annual) and where rates are not available for a particular village, a representative land rental rate based on the census block, district and then the state average, if necessary, is used.

Results

The results of the regression analysis are presented in Table 3. The first column is the base model which includes all inputs (as well as dummy variables for each input to allow for zero input quantities), sixteen state dummy variables, and four crop control variables but does not include any of the land fragmentation variables. As seen from the adjusted R-square, the base model is able to explain nearly 77 percent of the variation in the value of agricultural output.

In columns #2-6 we consider the role of land fragmentation using the various different measures discussed earlier and test whether the inclusion of land fragmentation variables is a statistically significant contribution over the base model. For comparison the model estimates having included Simpson's Index are presented in column #2. Although we have shown that Simpson's muddles the impact of number of fragments and variability in fragment area, we do find that land fragmentation when captured by this measure does have a negative impact on productivity (significant at the 95% level). The LR test comparing the base model with the model in #2 does suggest an improved model. However, without separating the affect of fragment number and variability in fragment area, it is difficult to ascertain what aspect of land fragmentation is the main culprit.

To look at the impact of number of fragments and variation in fragment area we consider those model estimates in columns #3 and #4. Since our decomposition of Simpson's index earlier in the text shows a non-linear relationship in the number of fragments, in column #3 we include the (log of) number of fragments as well as its square. With both the level and quadratic terms significant at the 99 percent level, the LR test implies this model is a significant improvement over the base. Due to the quadratic term the significance of this variable requires it be evaluated at a particular point on interest in the sample, usually at the mean or quantiles, and will return to this shortly. In column #4 variability in fragment area is added and we find this measure has a statistically insignificant impact on productivity and does not improve the model fit as indicated by the LR test. Based on these results in columns #3 and #4 leads us to infer that numbers of land fragments is more the more relevant of these two types of fragmentation when explaining productivity.

Using the unique distance data collected in the REDS survey we are able to compute the effective distance measure referred to earlier and include this as an explanatory variable in both linear and quadratic form in column #5. Comparing against the base model we find that inclusion of the distance measure significantly improves the model in comparison to the base. Like with the number of fragments, since the distance measure appears enters partially as a quadratic, inferring the significance of this variable will require evaluation at a particular point.

Having found that number of fragments and distance appear to be important land fragmentation factors (at least in a model superiority sense), our next step involves introducing both of these variables and the results of this are presented in column #6. Again we find the model is superior to the base model as indicated by the LR test. To interpret the significance of fragmentation we use the estimates presented in column #6 to evaluate at different points in the sample: i) the responsiveness of output with respect to fragmentation variable (i.e. elasticity); and ii) the economic significance a 10% change in the fragmentation variable on output.

The elasticities reported in Table 4 are shown when evaluated at each quartile and the mean. At each these points the usual tests statistical significance are carried out using standard errors obtained using the Delta method. In the upper half of the table we report the elasticities for the responsiveness of output to change in number of land fragments, and the lower half pertains to change in distance measure. At the first quartile (25th percentile), the output elasticity with respect to number of fragments is negative and significant (at the 1% level), and then insignificant at the 50th percentile and at the mean. For the distance measure, the elasticity with respect to output remains negative from the 25th to 75th percentile and is significant at the 1% level at each of the points reported. Unlike for number of fragments, the output-distance elasticity increases (becomes less negative) slightly from the 1st to 3rd quartile due to a relatively small estimate for the quadratic term.

Interpreting these results in a more meaningful manner, the last two columns in Table 4 report the predicted change in the value of output resulting from a 10 percent decrease in the land fragmentation variable. For number of fragments, our results indicate a decrease in the number of fragments for the representative farmer from an average of 2 to 1.8 fragments will increase the value of output by 13.4 Rs. per fragment (or 26.8 Rs./acre). Due to the positive estimate for the quadratic term, the change in output value will continue to become smaller and small as one moves closer to the 50th percentile. At the 50th percentile and upwards, the value of output actually decreases but is of no concern since the majority of farmers have 3 fragments or fewer and the reliability of the model becomes less and less as we approach regions in the dataset where observations are sparse. In the case of distance measure, we find the per acre benefit is generally in the range of 20-24 Rs. between the first and third quartiles.

In general the productive benefit from reducing either of the fragmentation variables is relatively small in economic terms, although these may be statistically significant over certain ranges within the data. To provide a little perspective, reducing distance measure by 10 percent implies reducing the average distance to the home plus other fragments by roughly 80 meters on average. The gain from this is 47 Rs. per fragment (21 Rs./acre) and represents a value equal to ¼ of 1 percent (47/18593) of the average value of output. In this case whether or not a program to reduce effective distances between fragments would have to balance the costs of implementing such a program with the discounted stream of benefits from reducing effective distance. With a discount rate of 5 percent, the benefit to be weighed against the program cost would be (47/0.05) 420 Rs. per acre.

Discussion and Concluding Comments

Our analysis involves using a unique household survey which includes detailed information on land fragments including distances between other fragments among others. Analyzing the impacts of alternative fragmentation measures, the results of the current analysis indicate that while certain measures of land fragmentation do appear to adversely affect production, in economic terms these impacts actually appear somewhat small. Given limited benefits to further reducing land fragmentation this begs the question as to whether or not further efforts to reduce fragmentation will result in a net societal gain. This is a particularly important question since accounts of land consolidation programs in India appear to be rather costly in terms of time and hindered by a number of adverse selection and agent/agency problems (Uttar Pradesh – Oldenburg 1990). Ultimately, whether there is potential for a net gain is an empirical question. This paper presents some of the benefits, further analysis should be directed to assessing the cost.

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Table 1. Degree of fragmentation and subdivision within fragments: total and by state

	Number of fragments		Number of subdivisions/ fragment		Number of obs.
Total*	3.17	(2.04)	1.87	(1.68)	8879
State					
ANDHRA PRADESH	2.15	(0.84)	1.22	(0.45)	387
BIHAR	4.91	(2.27)	1.78	(1.36)	249
CHHATTISGARH	4.68	(3.71)	1.80	(1.27)	680
GUJARAT	1.26	(0.44)	1.00	-	369
HARYANA	3.41	(1.51)	4.39	(2.66)	713
HIMACHAL PRADESH	4.81	(2.09)	1.60	(0.94)	344
JHARKHAND	3.65	(1.75)	1.35	(0.93)	272
KARNATAKA	2.27	(1.43)	1.10	(0.36)	782
KERALA	3.48	(2.63)	1.29	(0.51)	42
MADHYA PRADESH	3.54	(1.84)	1.82	(1.43)	955
MAHARASHTRA	2.19	(1.14)	1.04	(0.21)	469
ORISSA	2.68	(1.76)	1.58	(0.98)	384
PUNJAB	2.91	(1.34)	3.91	(2.80)	275
RAJASTHAN	3.09	(1.51)	2.32	(2.00)	902
TAMIL NADU	1.97	(1.09)	1.51	(1.05)	229
UTTAR PRADESH	3.42	(1.77)	1.49	(1.07)	1569
WEST BENGAL	2.41	(1.28)	1.69	(0.77)	258

*Numbers based on land fragments used in the final analysis (standard deviations in parentheses).

Table 2. Summary Statistics

Variable	**Mean**	**Std. Dev.**		
Fragmentation variables				
Simpsons Index	0.47	(0.27)		
Number of Fragments	3.10	(1.95)		
Distances from fragment to all other fragments and household normalized by number of fragments	799.58	(934.34)		
Dissimilarity of fragment area	0.36	(0.41)		
Production and Inputs#	Mean	Std. Dev.	Rs./acre	Input Share*
Output	18594	(30164)	10325	
Seeds and Seedlings	1137	(3441)	601	0.062
Fertilizer	1931	(3642)	1225	0.111
Pesticides and Fungicides	396	(1538)	163	0.017
Bullocks	239	(694)	217	0.022
Implements and Mechanical	900	(1874)	601	0.061
Irrigation	243	(534)	212	0.019
Hired labor	1192	(2439)	722	0.067
Family labor	1562	(2122)	1520	0.138
Land	8336	(47802)	4582	0.489
Other variables	Mean	Std. Dev.		
Fragment area	2.198	(18.76)		
Season				
1	0.556			
2	0.409			
3	0.035			
Crop				
Bajra	0.232			
Maize	0.053			
Paddy	0.302			
Wheat	0.065			
Other	0.348			

#All output and inputs are reported in value (Rs.) terms as described in the text.

* Input shares do not sum to one due to omission of an input category listed as “miscellaneous”.

Source: REDS dataset and author calculations.

Table 3. Regression Results

Dependent variable: (log) value of agricultural output	#1	#2	#3	#4	#5	#6
Variable[%]						
(log) Seeds and Seedlings	0.195***	0.195***	0.196***	0.196***	0.196***	0.196***
	(31.67)	(31.59)	(31.68)	(31.68)	(31.79)	(31.80)
(log) Fertilizer	0.142***	0.142***	0.142***	0.142***	0.142***	0.142***
	(21.88)	(21.93)	(21.89)	(21.85)	(21.89)	(21.93)
(log) Pesticides and Fungicides	0.034***	0.034***	0.035***	0.034***	0.036***	0.036***
	(4.53)	(4.53)	(4.62)	(4.50)	(4.74)	(4.86)
(log) Bullocks	0.100***	0.098***	0.099***	0.101***	0.099***	0.097***
	(8.85)	(8.57)	(8.67)	(8.88)	(8.75)	(8.54)
(log) Implements and Mechanical	0.105***	0.105***	0.105***	0.106***	0.106***	0.106***
	(13.15)	(13.11)	(13.13)	(13.16)	(13.18)	(13.17)
(log) Irrigation	0.012*	0.012*	0.013*	0.013*	0.013*	0.014**
	(1.76)	(1.72)	(1.81)	(1.76)	(1.86)	(1.91)
(log) Hired labor	0.094***	0.094***	0.093***	0.093***	0.093***	0.092***
	(14.81)	(14.90)	(14.69)	(14.77)	(14.69)	(14.56)
(log) Family labor	0.105***	0.104***	0.106***	0.106***	0.105***	0.105***
	(16.44)	(16.15)	(16.34)	(16.45)	(16.36)	(16.26)
(log) Land	0.407***	0.406***	0.406***	0.407***	0.408***	0.408***
	(56.23)	(56.23)	(56.19)	(56.22)	(56.41)	(56.39)
Simpsons Index		-0.047**				
		(-2.11)				
(log) Number of Fragments			-0.083***			-0.095***
			(-3.13)			(-3.49)
((log) Number of Fragments)^2			0.042***			0.046***
			(3.17)			(3.46)
(log) Distance measure[#]					-0.061***	-0.049
					(-2.04)	(-1.59)
((log) Distance measure)^2					0.003	0.002
					(1.17)	(0.71)
Fragment area variability				0.011		
				(0.76)		
Constant	0.666***	0.709***	0.698***	0.663***	0.914***	0.919***
	(7.38)	(7.66)	(7.54)	(7.33)	(7.01)	(7.03)
State controls	yes	yes	Yes	Yes	yes	yes
Crop controls	yes	yes	Yes	Yes	yes	yes
LR-test: Model different than #1?		4.48**	10.36***	0.58	25.31***	37.90***
Number of observations	14960	14960	14960	14960	14960	14960
Adj R-square	0.768	0.768	0.768	0.768	0.768	0.768

Source: Authors estimates

Notes: i) Test statistics are in parentheses; ii) Significance is indicated by *, **, and *** for the 10%, 5%, and 1% levels respectively; iii) all variables for which the log is not defined (i.e., in the case of a zero input value) have a value of zero imputed and a dummy variable with value equal 1 is also included in estimation (these dummy variables for all traditional inputs are suppressed).

[%] Also included but not reported in this table are dummy variables to act as intercept shifters for each of the physical inputs where no (zero) input is reported as described in Equation 1.

[#] While not reported here, a dummy variable is also included in the estimation to account for the trivial case where the distance is equal to zero and a value of 1 imputed to allow the taking of logs in the same fashion as for inputs with zero input.

Table 4.Elasticity and Output response to a 10% reduction in land fragmentation variable

Land fragmentation variable	Percentile	N^{th} Percentile for:			Elasticity	Predicted change in output (Rs.) #	
		Frag. var.	Output	Area		Per fragment	Per acre
Number of land fragments	25^{th}	2	3500	0.5	-0.031*** (-2.52)	13.41	26.82
	50^{th}	3	9000	1	0.006 (0.52)	-0.94	-0.94
	75^{th}	4	21000	2.12	0.032** (2.06)	-60.66	-28.61
	Mean	3.1	18593	2.20	0.008 (0.76)	-7.68	-3.49
Distance measure	25^{th}	350	3500	0.5	-0.027*** (-4.35)	10.12	20.024
	50^{th}	600	9000	1	-0.025*** (-3.58)	23.99	23.99
	75^{th}	1000	21000	2.12	-0.023*** (-2.63)	51.37	24.23
	Mean	828.9	18593	2.20	-0.024*** (-2.99)	47.10	21.43

Source: Authors estimates

Notes: i) Elasticities are based on the estimates provided Model #6 of Table 3; ii) statistical significance of elasticities are computed using the formula described in the text and with estimated standard errors (t-statistic in parentheses) obtained using the Delta method; iii) Significance is indicated by *, **, and *** for the 10%, 5%, and 1% levels respectively.

For a reduction in the land fragmentation variable(z) to α of the original value (α<1), the change in output is computed as $\hat{y} - y$ where $\hat{y} = \exp\{\beta_1 * \ln(\alpha) + \beta_2 * [[\ln(\alpha z)]^2 - [\ln(z)]^2] + \mathrm{y}\}$ and $\beta_1$and $\beta_2$are the estimates associated with the linear and squared land fragmentation variables respectively.