Land Trade and Development: A Market Design Approach

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Abstract

Small farms and fragmented plots are hallmarks of the agricultural sector in less-developed countries and there is evidence of high potential returns to land consolidation and reallocation. Yet reaching an efficient land allocation through private bilateral trade is difficult and slow, due to complementarities, hold-up and asymmetric information. Market design therefore has the potential to improve the allocation of land and contribute to the development process. The design needs to address the specific market failures thought to be impeding land trade, as well as to be understandable to participants, many of whom may be poor and have limited education or experience in trading large assets. As a first step in this agenda we present the results of a series of framed field experiments with farmers in Kenya, comparing the performance of a range of two-sided land auction designs. Our results show that farmers were able to achieve high degrees of efficiency, and to comprehend and gain from a relatively complicated package auction design.

1 Introduction

Increasing agricultural labor productivity is key to reducing cross country income disparities. This is because poor countries are relatively less productive in agriculture and

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allocate the bulk of workers to agriculture. Recent work supports a conjecture that a poor allocation of agricultural land may play an important role in determining agricultural labor productivity. Labor productivity is increasing in farm size, but pour countries have much smaller farms (Adamopoulos and Restuccia 2014), there is direct evidence of increasing returns at the plot level in India with the advent of mechanization, but farmers do not operate at the optimal scale (Foster and Rosenzweig 2011), and some work suggests high degrees of heterogeneity in farmer productivity, but very low correlation between farmer productivity and land holdings (Restuccia 2016).[1]

While a great deal of work has investigated the role of secure property rights in allowing trade to efficiently allocate land (for a review see Besley et al. 2010), little work in economics considers how the market for land should be designed. We argue that both theory and evidence implies that efficient trade requires *both* secure property rights *and* a careful consideration of market design, and take some first steps toward understanding appropriate market designs.

Formal empirical evidence from the US shows that even in the presence of secure property rights, uncoordinated land markets may take decades to reach efficiency. Bleakley and Ferrie (2014) study land openings on the Georgia Frontier. In the early 19th century, land was allocated to settlers according to lottery. Allocated plots were of arbitrary sizes that were unlikely to be optimal in all (or even any) locations. Bleakley and Ferrie show that 80 years later, plot sizes correlate nearly one to one with allocated plot sizes and that the correlation does not disappear until 150 years after the initial allocation. These results show two things: first, that the correlation eventually disappears implies that the initial allocation was not optimal, and second, the persistence shows that, even in the presence of one of the strongest property rights systems in the world (the US), uncoordinated land trade leads to efficient reallocation only very slowly. Bleakley and Ferrie estimate that the initial misallocation reduced land prices (and hence productivity) by 20%.

[1] Some of these results may seem at odds with the large literature on the inverse relationship between farm (or plot) size and output per hectare, and the potential gains from equalizing land holdings. (see, e.g., Deininger and Feder (2001)). There are several key issues/differences. First, we are interested in labor productivity, envisaging a potential move of labor out of agriculture, while much of the literature is concerned with land productivity, presumably assuming that the population cannot move out of agriculture. Second, reallocating land to more efficient farmers may be inequality reducing if poorer farmers are more efficient. Third, the advent of mechanization seems to have removed the inverse plot size productivity relationship in India, and the existence of mechanization may itself be endogenous to the size of land holdings.

Anecdotal evidence from land consolidations programs in Europe also suggest that formal property rights are insufficient to allow farmers to make all the trades they desire. Throughout the currently developed world (Europe and the US), agriculture was at some point characterised by severe fragmentation: farmers owning multiple small plots of land. At least since the mid 1700's this fragmentation has been dealt with through government land consolidation programs.[2] This fact alone suggests demand for a more centralized market, but the most compelling evidence comes from the Danish case (see Hartvigsen 2014 for a review of the institutions). In Denmark land consolidation is undertaken on a voluntary basis: no land holder has to participate in the trade. A group from the land office works with a "village" for a period of about 4 years to generate a new plan for the allocation of land, for everyone that accepts the new plan, contracts of sale are drawn up and executed simultaneously. Figure 1 below shows an example of the change in land structure resulting from one of these programs. The change is striking, and is made more so by two observations: first, Denmark's institutions clearly allow free trade of land even in the absence of the land consolidation program, and second, the trade is completely voluntary meaning that every land owner was happy with the the change. These two facts together suggest that farmers wanted to defragment their land, but were not able to do so without the help of a coordination mechanism.

Figure 1: Agricultural Plots in Oster Stillinge Village, Denmark Before and After Land Consolidation. Image taken from Hartvigsen (2014).

There are also clear theoretical reasons to expect that uncoordinated land markets

[2] The FAO have a nice review of land consolidation programs available at http://www.fao.org/docrep/006/Y4954E/Y4954E00.HTM

would not perform well. First, uncoordinated land markets in the presence of fragmentation and increasing returns at the plot level are likely to be very thin. The most advantageous trades will be those that create contiguous plots and so a buyer of land is limited to purchase from a very small set of possible sellers. This thinness will lead to Myerson-Satterthwaite type problems. Second, markets are likely subject to significant exposure risk. Suppose that it is always optimal to hold two contiguous plots and a farmer starts with two fragmented plots. This farmer will need to undertake two separate trades to defragment her plots, and the first trade may need to take place at a loss. If the farmer cannot guarantee that the second trade will take place (perhaps because of hold-out or simply because of changing circumstances) then she will rightly be reticent to engage in the first trade. Finally, the efficient set of trades is likely to be complex. Efficient trades often involve multiple parties in a chain and there are multiple different possible trades and trading mechanisms that could be used.

A centralized market design can solve each of the theoretical problems, and relative to the land consolidation programs described above, can likely do so in a more efficient and timely manner.[3] In particular a package auction with XOR bidding that allows for sufficiently complex packages increases market thickness by allowing farmers to bid on multiple consolidated farms independent of their initial allocation, removes the exposure problem by allowing all trades to take place at once, and reduces complexity because both chains and trading rules are defined by the auction environment.

Ultimately our goal is to determine whether a centralized market design implemented in a rural land markets can improve efficiency. A first key step is to demonstrate that the target population, which consists of small holder farmers with little formal eduction, is able to trade efficiently using potentially complex market mechanisms in a simplified setting. Toward this aim, we designed a simple land trading environment, and implemented a framed field experiment in rural Kenya.

Our environment was designed to capture several key aspects of rural land trading problem, but in a simplified setting. First, there are increasing returns at the plot level, so defragmenting land is efficient. Second, both farmers and land are heterogeneous in terms of productivity, and a complementarity means that efficiency requires more efficient

[3] We see the historical land consolidation programs as akin to the comparative hearings discussed in the market design literature on spectrum auctions (Milgrom 2004). Even if these institutions allocate goods efficiently (which is debatable), they are costly, time consuming and open to political intrigue.

farmers to farm more productive land. We are thus able to study the ability of different market designs to efficiently defragment land, and to efficiently sort land to its highest value use (or reduce land misallocation). Third, there is a potential for exposure risk in our environment, which we believe to be a characteristics of real land markets. The setting is, however, much simpler than a real land market. While typical land consolidation programs in Denmark have involved between 50 and 100 land holders each with more between 2 and 10 plots of land, in our environment there were only 12 plots of land, with each land holder starting out with 2 plots.

We implemented three different market mechanisms, each operated through a centralized computerized exchange. In our first treatment, farmers were able to trade single plots of land in a continuous double auction with a broker who facilitated communication between farmers (*CDA-Broker*). Our second treatment was identical to the first, except that farmers could also specify swaps – that is they could offer to buy (or sell) one plot of land conditional on selling (or buying) one piece of land (*CDA-Swap*). Our final treatment (*CDA-Package*) was the same as *CDA-Swap*, except that farmers could also make package offers with a maximum of 2 buys and two sells. That is, they could offer to sell (or buy) up to two plots of land conditional on buying (or selling) up to two plots of land.[4] Recent work by Goeree and Lindsay (2016) shows that package auctions of this type can significantly increase efficiency in a setting with exposure risk. In all our markets bids were XOR, so that farmers could make multiple bids without fearing that they would all be fulfilled at once. This should increase market thickness. Farmers were also able to freely communicate throughout the trading rounds.[5]

We show several key results in our environment. First, efficiency is high. Farmers were able to extract more than 70% of the total efficiency gains across all treatments. We believe this is an important result as it demonstrates that our target sample are able to understand the market and to trade. Second, we show that, as conjectured, the more complicated *CDA-Package* mechanism achieves higher efficiency, increasing efficiency by over 7% or 5.6 percentage points. This again shows that our target population are able to make use of complicated market design features that one may conjecture are too complex

[4] In our context additional packages (for example sell 3 and buy 3) have no theoretical value because optimal allocation are always owning two plots.

[5] We feel that communication would be part of any implementable auction design and so wanted to include this feature in our experiments.

in this setting. In some sense this result is surprising given the recent results in Goeree and Lindsay (2016) which show, in a related environment with undergraduates as subjects, that the efficiency gains of package auctions are mostly achieved by allowing free communication. Third, we show that farmers were able to reap most of the gains from defragmenting land, but fewer of the available gains from sorting farmers to their most efficient plots. Importantly all three mechanisms perform similarly in terms of defragmentation, but *CDA-Package* performs better at sorting farmers to their appropriate land. Finally, while there is significant variability in farmer's performance, a farmer's Shapley value is highly correlated with performance in the auction and explains nearly 90% of the variation in the data. This last result suggests that strategic risk from exposure plays little roll in our mechanisms, but we also show suggestive evidence that *CDA-Package* further reduces strategic risk.

2 Experimental Design

2.1 Overview

We conducted 48 sessions, each consisting of 6 farmers who played 8 auctions. Farmers were recruited by taking a census of two villages in Kiambu County, Kenya, and inviting individuals who identified as farmers, who owned land, and were between 18 and 55 years of age. Approximately 70 per cent of invitees attended sessions. Early pilots showed that females were more likely to attend than Males, so Males were oversampled from the census.

At the beginning of each session, farmers were randomly assigned a computer and an enumerator (or bidding assistant) who read the instructions to each subject in their preferred language. The enumerator remained with their assigned farmer for the duration of the experiment and acted as a bid assistant. Following reading instructions, their role was to answer any questions concerning the trading rules, calculate the surplus generated from any potential package upon request, and input bids into the computer system. Enumerators also recorded payments for each period and marked whether subjects communicated with the other subjects in a given auction. These enumerators were given three days training on the mechanics of the game prior to the first session. We were clear with the enumerators that they were not to suggest particular trades to farmers, and enumerators did not financially benefit from farmer performance.

After the instructions, farmers participated in one 15 minute practice period where they were encouraged to make bids into the system using the mechanism assigned to their session. In the sessions that allowed for packages, the enumerator encouraged their farmer to use all possible packages and to make multiple bids.

Farmers next participated in 8 auctions each lasting 10 minutes. As discussed in the interface section, subjects could see their current allocation and current bids on their own screen and all subjects could see the plots for which there was activity on a centralized screen. An additional enumerator was available in each session who acted as a "broker." The broker would take oral messages between any two farmers but was discouraged from actively organizing trades.[6]

Farmers had a 30 minute break after the fourth auction and were fed a light snack. Payments occurred at the end of each session using mobile payments. An experiment lasted about 3.5 hours and farmers received 483.3 shillings on average. This was roughly 1.5 days wage for the represented population.

2.2 Auction Environment

2.2.1 Production Functions

We designed a simple experimental environment to study two key aims: de-fragmentation; and efficient sorting. Fragmentation occurs if plots are not contiguous, and is conjectured to reduce productive efficiency. An effective market design should be able to de-fragment an initially fragmented allocation. An efficient market design should also be able to allow land to flow to the most productive farmer, leading to efficient sorting.

In each experiment 6 farmers traded 12 plots of land located on a simplified map. The map is presented in Figure 2. Each farmer was initially allocated two plots.

There were two dimensions of heterogeneity. First, there are three land types: blue land is the most productive, red the second most productive and green land the least productive. Second, there are three player types: high productivity farmers, medium

[6]We allow for oral communication in this experiment since we are interested in developing exchanges that can be used in conjunction with current institutions. Given that communication is a feature in our target environment we consider it an important part of our design.

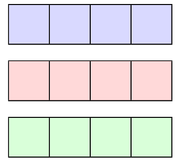


Figure 2: Map Representation of Available Land

productivity farmers and low productivity farmers. In all sessions there were two of each type of farmer. Panel A of Figure 3 shows total production profit for each farmer and land combination. In all cases the high productivity farmer earns twice as much as a low productivity farmer and a medium productivity farmer earns one and a half times. Red land is twice as productive as green land, and blue land is one and a half times as productive. This setup induces a complementarity. The gain for moving from green to blue land is 200 for a high type, but only 100 for a low type. Hence, efficiency requires the high type to farm the blue land, the medium type to farm the red land and the low type to farm the green land.

		Panel A: Profits			Panel B: Adjacency Bonus		
		Land Type			Land Type		
		Red	Blue	Green	Red	Blue	Green
Farmer Type	High	400	300	200	160	120	80
	Medium	300	225	150	120	90	60
	Low	200	150	100	80	60	40

Figure 3: Land and Farmer Types

In addition to the two dimensions of heterogeneity, there is a bonus for operating adjacent plots, and a cost from operating too-many plots. If a farmer operates two adjacent plots of the same colour they receive a bonus as shown in Panel B of Figure 3. A farmer who operates more than two plots of land earns profits equal to that of the two most profitable plots.

This simple setup allows for an increase in productivity from de-fragmentation (due to the adjacency bonus). The design also allows us to study sorting because there is a complementarity. The fact that a third plot is not productive gives us a way to study these issues with a simple to explain production function, but without the efficient outcome having all land owned by one farmer. This requirement was explained to participants as a simple span of control constraint, a farmer simply does not have enough time to tend to more than two plots.

The maps and production functions remained constant across all auctions. All players knew their own production function. They also knew that there were three types of players. They did not know the type of the other players in the room, and they were not initially informed who owned which plots.

2.2.2 The Initial Allocation of Types

We conjectured that the ease of achieving defragmentation and efficient sorting would depend on the initial allocation of plots. To study this issue, we created 8 different initial land allocations. The different allocations are shown in Figure 4. In each case, players 1 & 2 are high types, players 3 & 4 are medium types and players 5 & 6 are low types. The maps are symmetric within farmer type: players 1 & 2 are interchangeable, as are 3 & 4, and 5 & 6.

The allocations shown in Figure 4 are in order of our pre-experimental assessment of how difficult it would be to reach full efficiency. We considered four different dimensions of difficulty. First, for each individual, how many *CDA-Broker* trades are necessary to get to their efficient allocation. If an allocation requires two *CDA-Broker* trades, it requires only one *CDA-Swap* trade. If an allocation requires four *CDA-Broker* trades, it requires two *CDA-Swap* trades or one *CDA-Package* trade. Second, we considered how many people would need to be involved in any efficient *CDA-Swap* trade. Third, we considered whether money is required to reach an efficient trade. Finally, we considered strategic issues, for example the propensity to hold-out.

Map 1 is the simplest map. For each player reaching efficiency requires only one *CDA-Swap* trade and only two individuals are involved in that trade. No money is required because all efficient trades increase all participants surplus equally. Map 2, is similar to Map 1, but money is required because efficient trade for some participants reduce their surplus. Map 3 is similar to map 1 and in principle requires no money. However, players 2, 4 and 6 appear to have a strategic motive to holdout. Map 4 can be solved

Map 1

Optimal Owner	Endowment			
(1,2) – BLUE	1	2	1	2
(3,4) – RED	3	4	3	4
(5,6) – GREEN	5	6	5	6

Map 2

Optimal Owner	Endowment			
(1,2) – BLUE	1	3	2	5
(3,4) – RED	4	6	1	3
(5,6) – GREEN	2	5	4	6

Map 3

Optimal Owner	Endowment			
(1,2) – BLUE	1	2	2	1
(3,4) – RED	3	4	4	3
(5,6) – GREEN	5	6	6	5

Map 4

Optimal Owner	Endowment			
(1,2) – BLUE	1	3	2	4
(3,4) – RED	3	5	4	6
(5,6) – GREEN	5	1	6	2

Map 5

Optimal Owner	Endowment			
(1,2) – BLUE	3	5	4	6
(3,4) – RED	1	5	2	6
(5,6) – GREEN	1	3	2	4

Map 6

Optimal Owner	Endowment			
(1,2) – BLUE	5	6	5	6
(3,4) – RED	1	2	1	2
(5,6) – GREEN	3	4	3	4

Map 7

Optimal Owner	Endowment			
(1,2) – BLUE	5	6	6	5
(3,4) – RED	1	2	2	1
(5,6) – GREEN	3	4	4	3

Map 8

Optimal Owner	Endowment			
(1,2) – BLUE	1	2	3	4
(3,4) – RED	3	4	5	6
(5,6) – GREEN	5	6	1	2

Figure 4: Initial Land Allocations

with only one *CDA-Swap* trade per player, but those trades have to have at least 3 people involved. Money is required, but there is no strategic motive apparent. Map 5 is more complex, each participant must make two *CDA-Swap* trades, or one *CDA-Package* trade. Each of those trades involves only two players, money is required and their does not appear to be a strategic motive. Map 6 again requires two *CDA-Swap* trades, but in this case, some of those trades require at least 3 participants. Again, money is required and their does not appear to be a strategic motive. Map 7 is similar to map 6 but appears to have a holdout problem. Finally, we judged map 8 to be the most complex. It requires two *CDA-Swap* trades per player and some of those trades require at least 4 participants, and may require all parties to participate.

It should be noted that in coming to our ex-ante assessments of difficulty we tried to determine how hard it would be to reach full efficiency. We did not consider whether initial allocations differed in the ease with which partial efficiency could be achieved. We return to this point below.

2.2.3 Cash Constraints and Exposure Risk

Building on the work of Goeree and Lindsay (2016) we conjectured that a key impediment to trade would be exposure risk. Paraphrasing Goeree and Lindsay, there is exposure risk if reaching a desired allocation requires at least one player to make a loss on an early trade. This potential loss may make the trader reluctant to make the first trade if subsequent trades may not happen.

For example, consider the following initial allocation where high type player 1 wishes to buy high productivity land from medium type player 3 and 4, and sell medium productivity land to them. The initial and efficient allocations are:

3	4		
3	1	1	4

and

1	1		
3	3	4	4

Initially the land values are 720, 525 and 525 for 1, 3 and 4 respectively, while after trade they are 960, 540 and 540 so there exists a sequence of trades that is mutually beneficial. However, if 1 first buys from 3, he holds three plots and cannot farm all of them. In fact, because of the adjacency bonus to his medium quality land, his intermediate landholding is still worth 720, while farmer 3's has decreased to 225. Since the surplus from this trade is negative (-300), at least one of 1 and 3 must make a loss on the trade. Similarly, if 1 first sells to 3, 1's land value decreases to 300 while 3's increases to 540. The net gain is negative (-285) and one must make a loss on the trade.

There are several reasons why simple trades may have negative surplus in our setting. First, as in the example, the purchased plot may not initially be farmed because the buyer already has two plots, so output is lost until the buyer sells another plot (this is the perfect substitutes feature of the production function). Second, the buyer may produce less from the purchased plot than the seller because of type productivity differences. Third, the sale might break up a previously consolidated plot.

We additionally introduced an experimental design feature (cash constraints) to increase the likelihood that trades suffer from exposure risk. In half of all auctions, farmers started with cash of 750. This would be sufficient to compensate a high productivity farmer with two consolidated high quality plots for selling one - (land value before is 960, after is 400, a difference of 560). In the other half, the cash endowment was 250. This is only enough to compensate a high type for an unconsolidated low quality plot, a medium type for an unconsolidated medium plot or a consolidated low plot, or a low type for an unconsolidated high plot or any other plot.

As a result in a low cash treatment in some positive surplus trades one party must make a loss. For example, consider the following initial allocation where 1 and 3 own only one plot of medium quality land each.

1	3		

If 1 sells to 3 the surplus is positive (40). However the plot is worth 300 to 1, so 3 may not be able to compensate him.

2.2.4 Trading Mechanisms

We consider three trading mechanisms each based on the continuous double auction: a simple *CDA-Broker* mechanism where farmers can communicate via the broker but can place only buy or sell orders to the market, a *CDA-Swap* mechanism where subjects can place buy orders, sell orders, or packages orders consisting of one sale and one purchase, and a *CDA-Package* mechanism where subjects can place buy orders, sell orders, and package orders consisting of up to two sales and two purchases. Communication through the broker is available in all three mechanisms and there are no other differences in the market mechanism other than the packages that are allowed.

Our mechanisms are based on the winner determination rule and surplus division rule outlined in Goeree and Lindsay (2016) with some modifications that were made to allow for larger packages.[7] As in their mechanisms, let the set of farmers, $\mathbb{F}$, be indexed by $i \in \{1, \ldots, 6\}$ and the set of plots, $\mathbb{L}$, be indexed by $l \in \{1, \ldots, 12\}$. Farmers submit *orders* $o = (m, x)$ consisting of the minimum amount of money they must receive, m, and a vector of demanded plots, $x \in \{-1, 0, 1\}^{12}$. A negative number indicates that a farmer is offering money or is offering to sell a plot while a positive number indicates that a farmer must receive money or wants to buy a plot. For instance, an order of $(-500, \langle 1, 0, ..., 0 \rangle)$ indicates that a farmer is willing to pay up to 500 points in order to acquire plot 1 while an order of $(0, \langle 1, -1, 0, ..., 0 \rangle)$ implies that the farmer is willing to buy plot 1 and sell plot 2 as long as he pays no money.

Orders placed by a farmer must be *legal*. Denote the plots owned by farmer i at time t as $\omega_i^t \in \{0, 1\}^{12}$ and denote the cash of farmer i at time t as c_i^t. A bid (m, x) is legal if at the time of placing the order, $c_i^t + m \geq 0$ and $\omega_i^t + x$ is either zero or one in all dimensions. A bid is thus legal if the farmer has more cash than the amount of money he offers, he sells only land that he owns, and he buys only land that he does not own. Orders placed by a farmer are also restricted by the mechanism used in each treatment as outlined above.

Legal orders are sent to the order book in the order that they arrive and transactions occur any time that there exists a set of legal orders where (i) supply equals or exceeds demand for all plots, (ii) only a single order is used for each farmer, and (iii) the total amount of money demanded in the set of bids is less than zero. Formally, let $\mathbb{O}^t$ denote

[7] Their continuous auction design is in turn influenced by the RAD design of Kwasnica et al. (2005).

the legal orders in the order book at time t and index its elements, $o_j = (m_j, x_j)$, by $j = \{1, \ldots, |\mathbb{O}^t|\}$. Let $d = \{0,1\}^{|O^t|}$ be a vector of orders from the order book, where $d_j = 1$ if an order j is winning and $d_j = 0$ otherwise. Let $\mathbb{O}_i^t$ be the active orders of farmer i and let $\mathbb{W}_i = \{o_j \in \mathbb{O}_i^t | d_j = 1\}$ be the orders of farmer i that are winning.

At each time t we find:

$$V^* \equiv \max_d \sum_j -m_j d_j$$

subject to

$$\sum_j x_j^l d_j \leq 0 \qquad \forall l \in \mathbb{L}, \quad \text{and}$$
$$|\mathbb{W}_i| \leq 1 \qquad \forall i \in \mathbb{F}.$$

Trade is triggered if $V^* \geq 0$.[8]

When a transaction is triggered, we return plots that were not demanded back to their original owners and transfer all other plots according to the set of winning orders. If there is a positive surplus (i.e., $V^* > 0$), we divide the remaining surplus amongst the winning farmers as follows: let $\mathbb{W} = \{o_j \in \mathbb{O}^t | d_j = 1\}$ be the set of winning orders and $\widehat{\mathbb{W}} = \{o_j \in \mathbb{O}^t | o_j \in \mathbb{O}_i^t, |\mathbb{W}_i| = 1\}$ be the set of all orders made by the winning farmers. Likewise, denote the set of orders made by non-winners by $\mathbb{NW} = \mathbb{O}^t \setminus \widehat{\mathbb{W}}$. Let $p \in \{0, \ldots, 10000\}^{12}$ be a vector of (integer) prices and denote the surplus generated by order j at prices p as $s_j(p) = -m_j - p \cdot x_j$.[9]

As is standard in these problems, we find the set of prices that lexicographically maximizes the minimum surplus of winning farmers subject to the revealed preference

[8]Note that the restriction of legal trades ensures that there is no short selling and that all budget constraints are met. We handle these on the client side to minimize the computation time of the winner allocation problem. Relative to Goeree and Linday (2016), the additional cardinality constraint prevents more than one order from a farmer being used in each transaction. This constraint ensures that orders submitted by each farmer are considered XOR.

[9]We use integer prices in the experiment in the range of 1 and 10000 so that trade prices are similar to ones that farmers are likely to encounter when buying and selling goods in Kenya Shillings on a day-to-day basis.

constraints of the losing orders.[10] Finding these prices is equivalent to solving:

$$\min_{p} \sum_{j} d_j \left[s_j(p) - \frac{V^*}{|\mathbb{W}|} \right]^2$$

subject to:

$$\begin{aligned} s_j(p) &\geq 0 \qquad \forall o_j \in \mathbb{W}, \\ s_j(p) &\leq 0 \qquad \forall o_j \in \mathbb{NW}, \quad \text{and} \\ \sum_j d_j s_j(p) &= V^*. \end{aligned}$$

Each winner pays or receives $p \cdot x_j$ and losing farmers pays and receive nothing. In the case of ties, we use the first solution found by the solver.[11]

As can be seen by the optimization rule above, lexicographically maximizing the minimum surplus is equivalent to minimizing the squared difference between the surplus of each winner and the equal split subject to an additional constraint that all surplus is allocated. We explain our surplus division rule using this logic. Farmers are told that we try to split the surplus as evenly as possible between the farmers but that we want to make sure that farmers who do not trade are not disadvantaged. In training our enumerators we gave two main examples — one where there is a single buy order and a single sell order and where the surplus is divided equally and one where there are two buy orders and a single sell order and where the non-winning buy order pins down prices.

After a transaction is triggered, we make all other non-winning orders made by farmers in the winning coalition inactive and allow them to renew any legal order that they might want to maintain. Orders that are made illegal (for instance, other orders that contain sales offer of objects no longer owned) are hidden from a farmer's offer book but can be renewed if later transactions make them legal. Farmers have the ability to

[10] The revealed preference constraints ensure that a losing farmer would not prefer to be winning once the surplus is reallocated given the information that was submitted to the market.

[11] The underlying algorithms were written in Minizinc, a free open-source constraint modeling language and solved using GECODE. In general, the winner determination problem could be solved in under 200 milliseconds for order books containing under 100 legal orders. The surplus division rule was slightly slower but usually completed in 600 milliseconds. To ensure that the system was able to continue in real time, we built timeouts into the surplus division rule that would end the solver and consume all the surplus if no solution was found in 10 seconds. This circumvented potential issues that could occur if prices weren't fully pinned down by the orders. In practice, we never had the timeouts trigger in a session.

withdraw legal orders at any time.

2.2.5 Interfaces

All bids were entered through a computer interface. The interface displayed the farmers basic valuations and current allocation on a geospatial map as in Figure 2, and provided a calculator that could be used to calculate the value of different allocations. Players (or their bidding assistant) could click on sets of plots on the map (depending on the treatment) and enter a willingness to pay or willingness to accept to make the trade. Only legal bids were accepted by the computer. The interface also showed a list of all current bids placed by that player. A screenshot of the individual interface is shown in Figure 5.

In addition to the individual interface, a projector showed a map indicating which plots of land were currently offered for sale, or had offers to purchase.

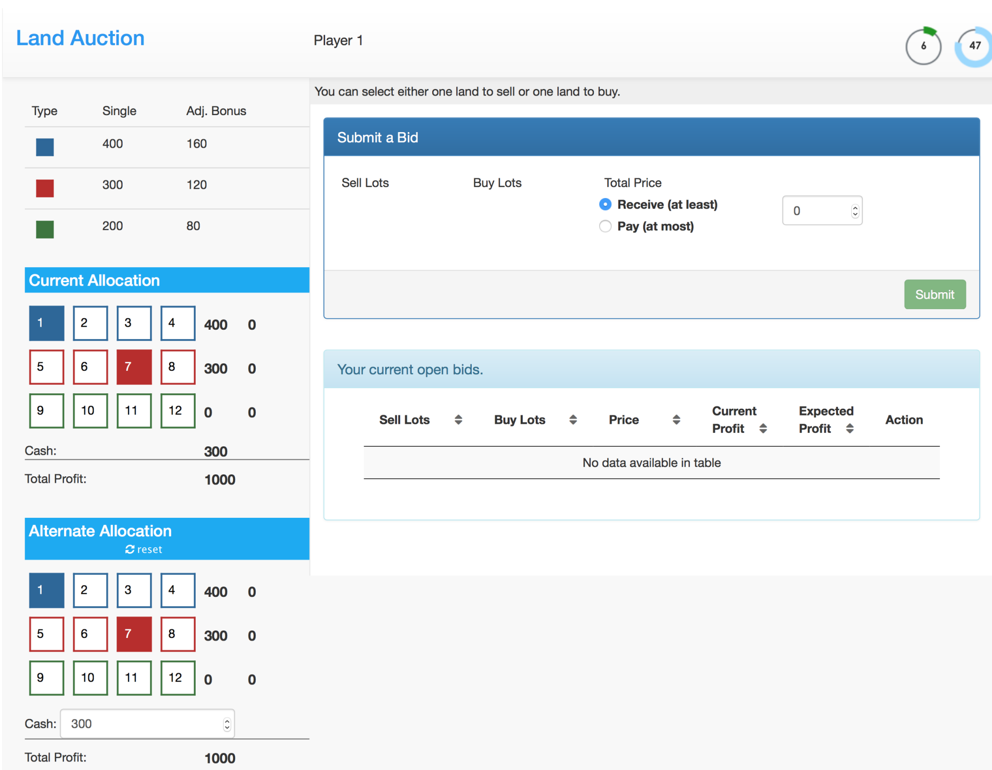


Figure 5: Computer Interface Used for Entering Bids

2.2.6 Treatment Randomization

We played 48 sessions in total. Each session consisted of 8 auctions and was assigned to one trading mechanism: *CDA-Broker*, *CDA-Swap*, or *CDA-Package*. In each session the first four auctions had the same cash treatment and the second four the alternative cash treatment. Hence, each session could be assigned to one of six possible treatments: $\{BrokerLH, BrokerHL, SwapLH, SwapHL, PackageLH, PackageHL\}$ where $BrokerLH$ denotes a *CDA-Broker* treatment that plays low cash for the first four auctions and then high cash for the last four. These treatments were block randomized. The set of 48 sessions was divided into 8 blocks each consisting of 6 consecutive sessions. The 6 treatments were then randomly assigned within the block.

Each lab session required one lead enumerator to introduce the environment and implement the computer programs, 6 bidding assistants to assist the players in making calculations and entering bids, and one broker. Two labs (labeled red and black) ran in parallel, each playing one session in the morning and one in the afternoon. Lead enumerators were assigned to a specific lab (red or black) and stayed in that lab throughout. Bidding assistants were randomly assigned to a specific player and lab (e.g. player 4 red) for each session. Brokers were randomly assigned to a lab for each session.

Because subjects arrived slowly over time (it was hard to get farmers to all arrive at 9am), the first session of the day alternated between the red and black lab. The first 6 farmers to arrive were randomly assigned to a player number between 1 and 6 and then played in the lab that was operating the first session. The next six farmers to arrive were similarly assigned a player number and played in the second lab. Each player played four auctions as their initial player number and was then moved to a different player number. Player 1 became player 3, player 2 become player 5, player 3 became player 1, player 4 became player 6, player 5 became player 2 and player 6 became player 4. Because of the symmetry within farmer type this sequence implies that every subject had an equal chance of being assigned to play one of the six possible sequences $\{HM; HL; MH; ML; LH; LM\}$.

Finally, the 8 maps displayed in Figure 4 were assigned to sessions. Every session played every map, and they were played in one of 8 orders. These orders were devised to minimize ordering effects: we wanted to have difficulty approximately even across the session to minimize the impact of learning effects. The 8 map orders are displayed in Figure 6. The maps orders were then randomly permuted, and the first session played the permuted map orders in order 1 to 6, the second session played the map orders 2 to 7 in order, etc.

Order 1	5	1	3	7	6	2	4	8
Order 2	7	3	1	5	8	4	2	6
Order 3	6	2	4	8	5	1	3	7
Order 4	8	4	2	6	7	3	1	5
Order 5	3	7	5	1	4	8	6	2
Order 6	1	5	7	3	2	6	8	4
Order 7	4	8	6	2	3	7	5	1
Order 8	2	6	8	4	1	5	7	3

Figure 6: Map Orders

Overall, this method gives assignment to the main auction treatments and cash treatments that are orthogonal to the other elements of the design, as well as maps that are assigned orthogonally to the treatments and also randomly across time and session. We also have balance across all main elements of the experimental design.

3 Results

3.1 Data Overview and Summary Statistics

Table 1 provides summary statistics for our sample. Despite oversampling men we had nearly 60% female participants, likely reflecting greater availability during daytime hours. Recall that each of these participants had indicated that they own land and are responsible for farming decisions on that land. Average age was 43 years, and the average attendee had about 12 years of school, indicating that our sample was slightly better educated than anticipated. Most farmers owned very little land (just less than 1 acre) and on average one plot. This low ownership of plots likely reflects the fact that many women own a small fraction of the family land. Very few of the farmers have every traded land.

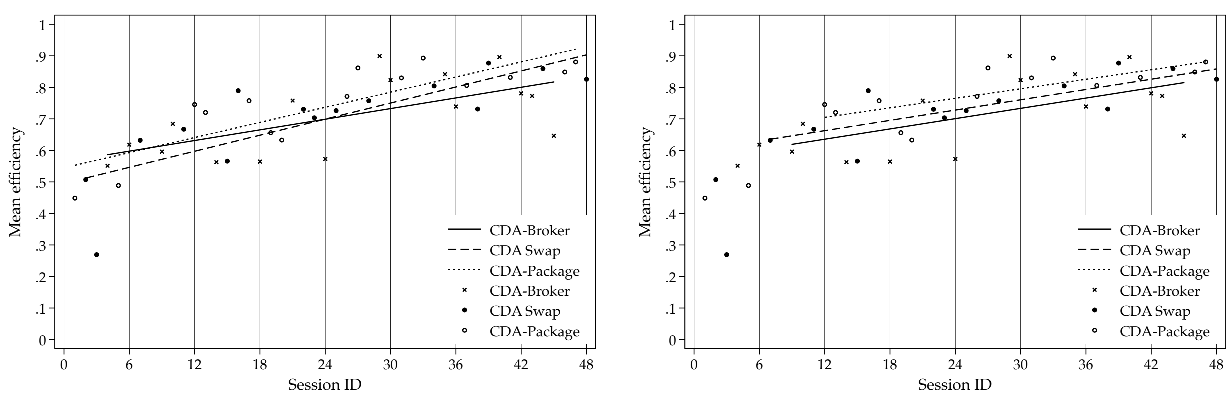
As discussed in the design section, we provided enumerators with 3 days of training prior to the start of the experiment where they learned how to use the interfaces, how to calculate payoffs, how to place bids, and how prices were set. In the training sessions, enumerators also practiced giving instructions to each other. Despite this training,

Table 1: Summary Statistics

	CDA-Broker	CDA-Swap	CDA-Package	Total
Female	0.604	0.633	0.520	0.586
	(0.489)	(0.482)	(0.500)	(0.493)
Age	42.93	43.28	41.49	42.56
	(11.31)	(9.324)	(10.51)	(10.46)
Education (years)	11.55	11.63	12.53	11.90
	(3.515)	(3.026)	(3.257)	(3.307)
Married	0.720	0.711	0.800	0.743
	(0.449)	(0.454)	(0.400)	(0.437)
Household size	4.034	3.953	4.217	4.068
	(1.759)	(1.685)	(1.630)	(1.696)
Employed	0.426	0.453	0.507	0.462
	(0.495)	(0.498)	(0.500)	(0.499)
Owned land (acres)	1.063	0.767	0.790	0.877
	(1.908)	(0.866)	(1.335)	(1.451)
# plots owned	1.252	1.279	1.259	1.263
	(0.524)	(0.623)	(0.573)	(0.573)
Bought/sold land last 12mo	0.0735	0.0222	0.0784	0.0583
	(0.261)	(0.148)	(0.269)	(0.234)
Risk aversion (1-10)	3.188	3.523	3.256	3.318
	(3.000)	(3.370)	(3.115)	(3.162)

Standard deviations in parentheses.

our lead enumerators raised concerns that the enumerators did not fully understand the rules of the package auctions in early sessions. As the enumerators were responsible for translating the instructions and teaching farmers, it is likely that farmers didn't fully understand the mechanisms in early treatments. Looking at the data, the first two sessions in each treatment accounted for 43% of observations where efficiency was in the bottom decile and accounted for all observations where efficiency was negative. Figures 7a and 7b show the evolution over time of efficiency, broken down by treatment.[12] Figure 7a shows that there is a marked improvement in efficiency over time for all treatments, but that this is much stronger for the more complicated package treatments. This makes sense if enumerators found those treatment difficult to explain. Figure 7b is the same as Figure 7a but a linear fit is added to the data only after block one. This figure shows that if we remove block one learning seems to be even across the three treatments.



(a) Linear fit including all Blocks

(b) Linear fit excluding Block 1

Figure 7: Mean Efficiency by Experimental Session

Given these observations we display all our results in three ways. First, we use all the data and no time trends. Second, we present results that exclude the first block of results. Third, we include a linear time trend. In all specifications we also include block (strata) fixed effects as well as controls for the gender composition of the session and the identify of the lab (red or black). Unless otherwise stated, we analyze the data at the auction level with errors clustered at the session level.

We lost one session due to the accidental reformatting of the server computers prior

[12]Efficiency is formally defined below.

to the session being backed up.[13] We also drop three sessions: one where a configuration was repeated and two where the wrong mechanism was used. In total our data consists of 366 sessions, 2928 auctions and 2196 farmers.

3.2 Efficiency

We begin our analysis of the data by studying how much of the potential gains from trade was captured by farmers. In each auction, we calculate efficiency:

$$E = \frac{\sum_{i=1}^{n} s_i^{final} - s_i^{initial}}{\sum_{i=1}^{n} s_i^{optimal} - s_i^{initial}} \tag{1}$$

where s_i^{final} is the surplus generated by farmer i's final land allocation, $s_i^{initial}$ is the surplus generated by farmer i's initial land allocation, and $s_i^{optimal}$ is the surplus generated by farmer i's land allocation at the group optimum. Efficiencies are bounded above by 1 and are never negative in the set of auctions that we analyze. We thus interpret efficiency as the percentage of possible gains that are realized in a given auction.

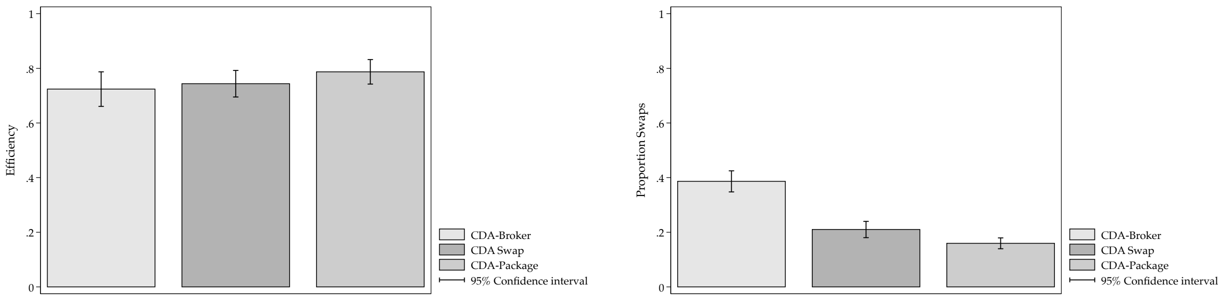
Result 1 *Average efficiency of all three treatments is above 70 percent. There is a 5 - 6 percentage point increase in efficiency in the* CDA-Package *mechanism relative to the* CDA-Broker *mechanism.*

Support for result one is given in Figure 8 and Table 2. Figure 8a shows average efficiency and 95% confidence intervals for each of the three market mechanisms.[14] As can be seen, average efficiency is high under all three mechanisms with an average efficiency rate of over 70% in all treatments.

The *CDA-Broker* mechanism has the lowest average efficiency of 70.9%. This efficiency is high relative to the work of Goeree and Linday (2016) who document poor performance of a CDA auction in a house auction with exposure risks. As indicated in

[13] Our experiments took place in a village where there was no internet access and we used two laptops as servers. Following the last session, these laptops were confused by staff with the computers we used as clients and the hard drives were formatted in order to reuse the machines for other projects. The last session run was not backed up.

[14] As with all auction level results, we report confidence intervals using errors that are clustered at the session level.



(a) Efficiency by Treatment

(b) Brokerage by Treatment

Figure 8: Efficiency and Brokerage levels Across Treatments

Table 2: Efficiency

	(1) Efficiency	(2) Efficiency	(3) Efficiency	(4) Efficiency	(5) Efficiency	(6) Efficiency
CDA Swap Auction	-0.006	-0.023	0.025	0.005	0.008	-0.010
	(0.031)	(0.041)	(0.030)	(0.044)	(0.029)	(0.040)
CDA Package Auction	0.044	0.052	0.056**	0.042	0.062**	0.071*
	(0.027)	(0.038)	(0.028)	(0.041)	(0.025)	(0.035)
Low Cash Treatment	-0.006	-0.012	-0.008	-0.030	-0.006	-0.012
	(0.022)	(0.043)	(0.023)	(0.048)	(0.022)	(0.043)
CDA Swap $\times$ low cash		0.035		0.040		0.036
		(0.053)		(0.058)		(0.053)
CDA Package $\times$ low cash		-0.018		0.029		-0.018
		(0.056)		(0.059)		(0.056)
Block fixed effects	X	X	X	X	X	X
Gender & Lab controls	X	X	X	X	X	X
Drop Block 1			X	X		
Linear time trend					X	X
N	366	366	318	318	366	366
R-squared	0.173	0.175	0.094	0.095	0.180	0.181
Control group mean	0.713	0.713	0.739	0.739	0.713	0.713

Standard errors clustered at session level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. "Efficiency" measures the fraction of the potential welfare increase realized in a given auction. Block fixed effects control for stratification block (8 in total). Gender and lab controls are a variable measuring the fraction of female participants and a lab dummy. Time trend controls linearly for session ID (takes values 1-48).

the introduction, a major difference in our designs is that we allow for communication between farmers through a broker, which allows farmers to mitigate exposure risk through informal agreements. Our auction periods were also 10 minutes while theirs were 3 minutes. The longer time period of our auctions likely helped farmers to find mutually advantageous exchanges.

To see how communication is likely to be influencing exchanges in each of our mechanisms, we look at the transaction level data. Based on observations from our pilots, farmers that negotiate deals through the broker typically submit offsetting bids at exactly the same price to the computer system. Such bids register in the system as having no surplus to divide (i.e., $V^* = 0$). We use the proportion of trades with zero surplus as a measure of brokered transactions.

Figure 8b shows that a very large proportion of trades are brokered in all three mechanism but that the proportion of brokered transactions are declining as the available package size grows. As can be seen, nearly 40% of transactions in the *CDA-Broker* treatment are brokered, while brokered transactions account for 20% of transactions in the *CDA-Swap* mechanism and just over 16% of transactions in the *CDA-Package* auction. All differences between the mechanisms are significant in a simple OLS regression with session-level clusters (p-value $< .01$ for all comparisons). This difference is not driven by a greater number of bids in the package auctions, in fact the package and swap treatments had fewer bids in all. Our data thus suggests partial substitution between communication and the extent to which packages can ameliorate exposure.

Table 2 reports the relative treatment effects of the three mechanisms using OLS. Our preferred specification is (3), which has block fixed effects and leaves out the first block as discussed above. Under this specification, the *CDA-Package* mechanism has significantly higher efficiency than the *CDA-Broker* mechanism. From a base of 74% efficiency, the *CDA-Package* mechanism increases efficiency by 5.6 percentage points, or 7.5%.

As discussed above, we also changed the amount of cash that farmers started with across configurations. This was designed to alter the degree of exposure risk. As can be seen in all specifications the low-cash treatment does not appear to statistically significantly affect efficiency, and this lack of an impact is the same regardless of the mechanism used. It should be noted that we have low power to detect these interaction effects.

To better understand the relationship between the three mechanisms, we also compare fragmentation rates and the optimal sorting of farmers to land across the three mechanisms. We define defragmentation similarly to our measure of efficiency as the change in the number of adjacency bonuses because of trading divided by the total change possible. Similarly we define the decrease in misallocation as the change in the proportion of plots held by the optimal owner, divided by the efficient increase in the number of plots owned by the optimal owner.

Result 2 *Defragmentation rates over 80% in all three auction formats with no statistically significant difference in defragmentation across the treatments. The treatments are less successful at reducing misallocation, with a 26% reduction in misallocation in the* CDA-Broker *treatment. There is weak evidence that the* CDA-package *treatment performs better, decreasing misallocation by a further 10 percentage points.*

Table 3 reports the treatment effects of our mechanisms on fragmentation. Looking at the control group mean, CDA-Broker achieves 84% of the possible adjacency bonuses. This fragmentation rate is surprisingly low, suggesting that subjects are effective at agglomerating land even in mechanisms that do not allow for packages. Somewhat surprisingly, the *CDA-Swap* mechanism has similar fragmentation rates to the *CDA-Broker* mechanism, suggesting that the ability to swap one piece of land for another did not significantly improve on the ability of farmers to eliminate fragmentation. The *CDA-Package* auction appears to have slight lower fragmentation than the other two treatments, but the differences are far from statistically significant.

Table 4 reports the treatment effects on the percentage reduction in misallocation. As seen can be seen from the control group means, the *CDA-Broker* mechanism increased the number of farmers owning their optimal plots by only 26% of the optimum. Relative to this there is no evidence that *CDA-Swap* performed better in terms of reducing misallocation, but there is some evidence (column 5) that *CDA-Broker* reduces misallocation by 10 percentage points more.

Taken together, our efficiency, fragmentation, and misallocation results suggest that there is a small improvement in performance in the *CDA-Package* auction relative to the other two formats and that this improvement in performance is being driven by an improvement in positive assortative matching. Relative to earlier studies, the difference in efficiency across our three mechanisms is small suggesting that communication and infor-

Table 3: Defragmentation

	(1) Defrag.	(2) Defrag.	(3) Defrag.	(4) Defrag.	(5) Defrag.	(6) Defrag.
CDA Swap Auction	-0.012	-0.057	-0.001	-0.057	-0.009	-0.055
	(0.027)	(0.038)	(0.026)	(0.042)	(0.027)	(0.038)
CDA Package Auction	0.014	0.012	0.031	0.010	0.017	0.016
	(0.024)	(0.032)	(0.025)	(0.035)	(0.026)	(0.034)
Low Cash Treatment	-0.011	-0.041	-0.004	-0.053	-0.011	-0.041
	(0.022)	(0.044)	(0.023)	(0.049)	(0.022)	(0.044)
CDA Swap $\times$ low cash		0.090		0.110*		0.090
		(0.056)		(0.061)		(0.056)
CDA Package $\times$ low cash		0.003		0.042		0.003
		(0.053)		(0.056)		(0.053)
Block fixed effects	X	X	X	X	X	X
Gender & Lab controls	X	X	X	X	X	X
Drop Block 1			X	X		
Linear time trend					X	X
N	366	366	318	318	366	366
R-squared	0.143	0.151	0.070	0.080	0.144	0.151
Control group mean	0.836	0.836	0.860	0.860	0.836	0.836

Standard errors clustered at session level in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01. “Defrag.” measures the fraction of the potential defragmentation achieved, i.e. the fraction of initially unrealized adjacency bonuses realized at the end of the auction. Block fixed effects control for stratification block (8 in total). Gender and lab controls are a variable measuring the fraction of female participants and a lab dummy. Time trend controls linearly for session ID (takes values 1-48).

Table 4: Decrease in misallocation

	(1) Δ Misalloc.	(2) Δ Misalloc.	(3) Δ Misalloc.	(4) Δ Misalloc.	(5) Δ Misalloc.	(6) Δ Misalloc.
CDA Swap Auction	-0.020	0.031	0.004	0.052	0.014	0.066
	(0.050)	(0.053)	(0.052)	(0.058)	(0.048)	(0.050)
CDA Package Auction	0.063	0.072	0.092	0.082	0.110**	0.120
	(0.058)	(0.088)	(0.063)	(0.097)	(0.054)	(0.075)
Low Cash Treatment	-0.017	0.023	-0.014	0.011	-0.016	0.024
	(0.039)	(0.049)	(0.042)	(0.056)	(0.039)	(0.048)
CDA Swap × low cash		-0.102		-0.097		-0.104
		(0.071)		(0.082)		(0.071)
CDA Package × low cash		-0.019		0.020		-0.020
		(0.103)		(0.110)		(0.103)
Block fixed effects	X	X	X	X	X	X
Gender & Lab controls	X	X	X	X	X	X
Drop Block 1			X	X		
Linear time trend					X	X
N	274	274	238	238	274	274
R-squared	0.100	0.104	0.089	0.094	0.128	0.132
Control group mean	0.262	0.262	0.270	0.270	0.262	0.262

Standard errors clustered at session level in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01. "Δ Misalloc." measures the fraction of potential misallocation eliminated, i.e. the fraction of plots that were initially not owned by farmers of the optimal type that were owned by farmers of the optimal type at the end of the auction. Block fixed effects control for stratification block (8 in total). Gender and lab controls are a variable measuring the fraction of female participants and a lab dummy. Time trend controls linearly for session ID (takes values 1-48). Note: misallocation defined as number of plots held by wrong farmer type. Initial misallocation is zero in maps 1 and 3.

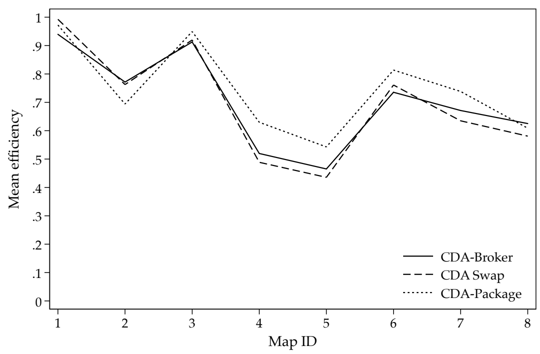
mal agreements is an imperfect substitute for packages. Looking deeper at the transaction level data, it appears that there is a substitution away from brokered trades and toward trades that utilize the centralized system as the ability to construct packages improves.

3.3 Efficiency and Initial Land Allocation

As discussed above, we conjectured that the ability to achieve full efficiency would depend on the initial allocation of plots and we tentatively ranked our 8 initial allocations in order of how hard we believed it would be to reach full efficiency. Figure 9 show efficiency, defragmentation and reduction in missallocation by initial allocation. In each case, F-statistics for a joint test of the hypothesis that all initial allocations perform the same are displayed below the figure.

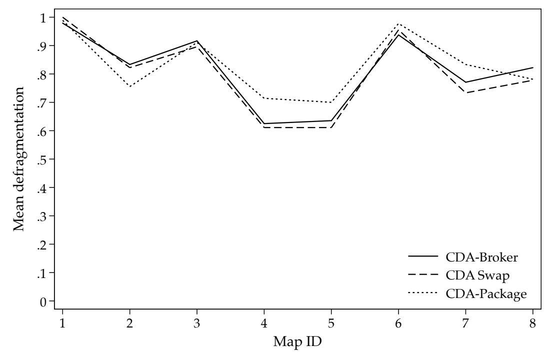
Result 3 *Efficiency gains depend on the initial allocation of plots, but are not monotonically decreasing in our pre-experimental assessment of difficulty.*

Overall the results support the hypothesis that the initial allocation is important for determining the level of efficiency reached. In each case that F-statistic suggests that there are significant differences across the maps. However, it is not the case that efficiency achieved is monotonically decreasing as we anticipated. In retrospect, we ranked maps by a conjecture on whether or not *full* efficiency would be reached. On this basis, we believed, for example, that map 8 was very hard, and map 5 less difficult. Inspection of Figure 9a, however, implies that this was not the case. Figures 9b and 9c give some idea as to why this is the case, map 8 was easy to defragment, but map 5 was not. Looking at the initial allocations (presented above in Figure 4) suggests why: for map 5 defragmentation (and efficiency) requires a *CDA-Swap* chain with three people involved. On the other hand, while full efficiency in Map 8 requires a *CDA-Swap* chain with at least 4 people, defragmentation requires only a *CDA-Swap* chain with 2 players. Thus 8 is easy to defragment and hard to remove misallocation, but 5 is hard to defragment. Because our auctions mostly reduced defragmentation, map 8 turned out to be easier than map 5. We leave further exploration of these issues for future work.



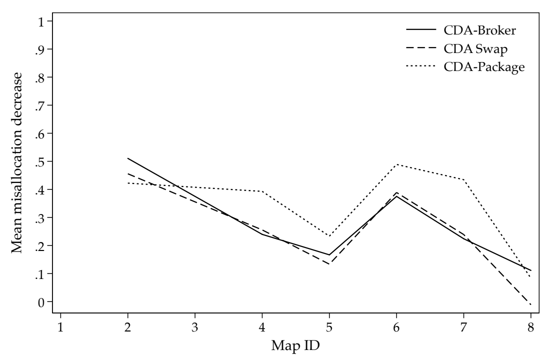
F-test for no difference in efficiency by map: $F(7, 45) = 30.45$, $p < 0.01$.

(a) Mean Efficiency



F-test for no difference in defragmentation by map: $F(7, 45) = 25.79$, $p < 0.01$.

(b) Mean defragmentation



Note: Initial misallocation = 0 in maps 1 and 3. F-test for no difference in reduction in misallocation by map: $F(5, 45) = 18.47$, $p < 0.01$.

(c) Mean improvement in misallocation

Figure 9: Efficiency, Defragmentation and Misallocation by Initial Allocation

3.4 The Division of Surplus

Thus far we have seen that efficiency levels are high across all of our mechanisms and that package mechanisms generate modest improvements in efficiency. A next question of interest is how the surplus is divided between participants. A natural concern in our setting is that some participants would not understand the mechanisms and may do particularly poorly, falling foul of exposure risk during trading.

At a fundamental level, the exposure problem is predicted to arise in our thin-market setting because there is limited competitive pressure and individuals are likely to bargain over the surplus on a transaction-by-transaction basis. An individual farmer who must make a series of transactions to agglomerate land or move to higher quality land may fear that investment costs made in early transactions will not be taken into account in subsequent interactions. Players that do not understand this issue face serious strategic risk.

In contrast, cooperative game theory suggests that coalitions are likely to be able to arrive at the Pareto frontier and that surplus division is based on the value that each individual brings to the grand coalition relative to the value that an individual brings when interacting with smaller coalitions. The cooperative model would thus suggest that the main drivers of surplus division is the value that an individual can generate in the various potential coalitions that could form, rather than strategic ability. If players reach a cooperative solution, there is little roll for the strategic risk that is our main concern.

A remarkable result in cooperative game theory shown in Shapley (1953) is that there is a unique division of surplus that arises under the reasonable axioms of symmetry, efficiency, linearity, and invariance to dummy players. In our environment, these Shapley values are constructed as follows: let v be a function from the set of all coalitions (2^6) to the set of real numbers R, which returns the maximal value that can be obtained by optimally reallocating the land owned by farmers in the coalition. The Shapley value of player i, is given by

$$\phi_i(v) = \sum_{S \subseteq \mathbb{F} \setminus \{i\}} \frac{|S|!(n - |S| - 1)!}{6!} (v(S \cup \{i\}) - v(S)), \tag{2}$$

where $\mathbb{F} \setminus \{i\}$ is the coalition of all farmers except for farmer i, and S is a subset of this coalition. The Shapley value can be viewed as the average surplus that a farmer adds over all possible permutations of the coalitions that can be formed. By construction $\sim_i \ \phi_i(v)$

add up to the value of the grand coalition, V^*.

As an initial exploration into the division of surplus, we construct the Shapley value for every individual and every auction. We take the total surplus available to any coalition S to be the total value of land held by the coalition when distributed efficiently. This definition excludes the cash that the players bring to the game. The Shapley value assumes that participants will reach efficiency, which is not the case in our experiments. To account for this, we scale the Shapley values in a given auction by the total surplus gained. This is equivalent to assuming that the share of surplus given to each player is the same as that suggested by the Shapley value, even away from the Pareto frontier.

Result 4 *The Scaled Shapley Value is a strong predictor of the shares received by farmers in all three mechanisms.*

Evidence for this result is shown in Figure 10 and Table 5. Figure 10 shows the tight fit between the Scaled Shapley Value and profit. In Table 5 the odd numbered columns show regressions with net profit as the left hand side variable and the Scaled Shapley Value as the explanatory variable. As above, our preferred specification (column 3) drops the first block and includes block and map fixed effects and gender and lab controls. The results are quite striking. First, the coefficient on the Shapley Value is almost exactly 1 and the intercept is very precisely estimates to be zero (in column 1), suggesting that on average the Shapley Value does an excellent job of predicting the distribution of surplus. Second, the R^2 is extremely high: in the regression without any fixed effects it is over 90%, suggesting that there is very little variability in the distribution that is not explained by the Shapley Value. This we see as the most important result: the Shapley Value suggests that there will be inequality in the division of surplus because different players make different marginal contributions (much as there is inequality in any competitive market), however, there is very little additional inequality generated by our game forms.

To investigate further the claim that there is little variation not explained by the Shapley Value, in the even columns in Table 5 we regress the squared residuals from the regression on the different mechanism treatments. Because *CDA-Package* should eliminate all exposure risk, we conjectured that there will be less residual variability in the *CDA-Package* treatments. The results provide weak support for this conjecture. The average of the squared residuals are reduced by around one quarter relative to *CDA-Broker*, and this

Table 5: Net Profit Regressed on Shapley Value

	(1) Net Profit	(2) Sq. resid.	(3) Net Profit	(4) Sq. resid.	(5) Net Profit	(6) Sq. resid.	(7) Net Profit	(8) Sq. resid.
Scaled Shapley	1.006***		1.006***		1.003***		1.006***	
	(0.005)		(0.005)		(0.005)		(0.005)	
CDA Swap Auction		24.102		-11.280		-1131.857*		10.263
		(878.928)		(761.663)		(671.227)		(700.333)
CDA Package Auction		-1092.844		-1100.135		-1140.044*		-1074.522*
		(655.227)		(663.968)		(649.872)		(634.812)
Low Cash Treatment		-498.028		-499.184		-317.761		-498.594
		(469.274)		(469.298)		(493.508)		(468.427)
Constant	-1.891							
	(3.174)							
Block fixed effects			X	X	X	X	X	X
Gender & Lab controls	X	X	X	X	X	X	X	X
Drop Block 1					X	X		
Linear time trend							X	X
N	2196	2196	2196	2196	1908	1908	2196	2196
R-squared	0.989	0.003	0.914	0.012	0.921	0.008	0.914	0.012
Mean dep. variable	542.311	3761.695	542.311	3761.568	546.947	3423.564	542.311	3761.562

Standard errors clustered at session level in parentheses. * p¡0.10, ** p¡0.05, *** p¡0.01. Block fixed effects control for stratification block (8 in total) and map fixed effects for the starting allocation map used (8 in total). Gender and lab controls are a variable measuring the fraction of female participants and a lab dummy. Time trend controls linearly for session ID (takes values 1-48).

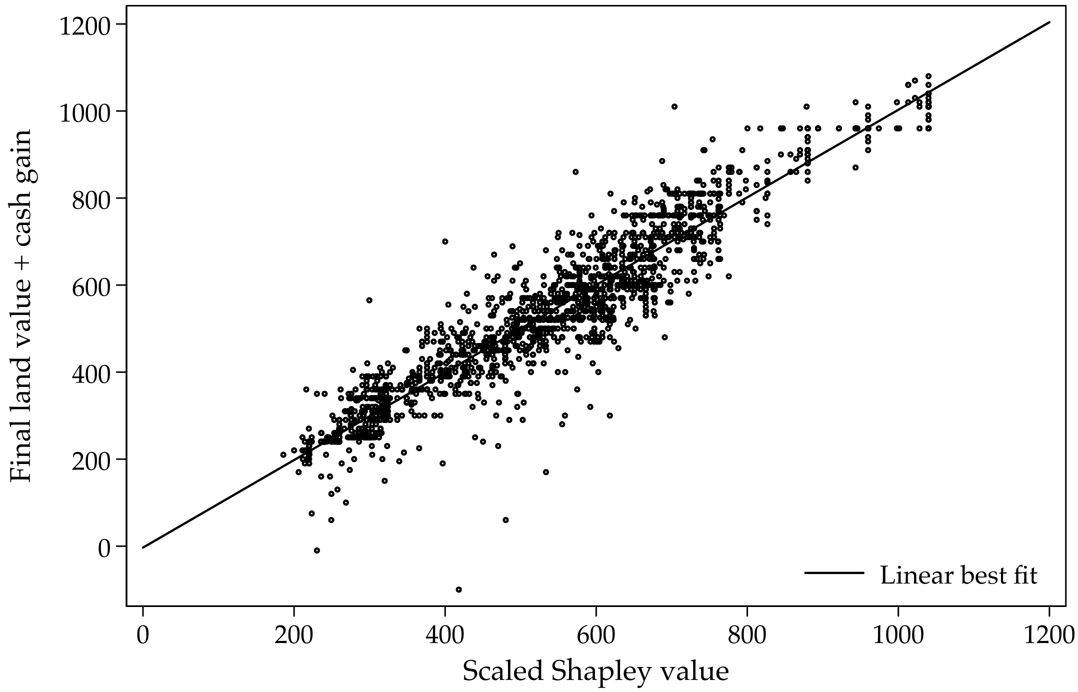


Figure 10: Scaled Shapley Values Predict Profit

effect is marginally significant in two of the four specifications presented in Table 5.

A final concern is that some players may lose money as a result of participating in land auctions. Overall, only 4.4% of auction player pairs end in a loss, and almost no players lost money across all 8 auctions.[15] There are no significant differences in the number of people losing money across the treatments.

Overall, our results suggest that farmers in our groups bargain quite effectively as a group and that bargaining is influenced by position in the ways predicted by the Shapley outcome. In addition to increasing efficiency there is weak evidence that our *CDA-Package* treatment also reduces strategic risk, suggesting that it is an improvement in both dimensions.

[15]These players were compensated with a show up fee, and so did not lose money as a result of participating in the experiment.

4 Conclusion

We implemented a framed field experiment in rural Kenya to understand the extent to which smallholder farmers can understand and benefit from a market design approach to land trade. Our results suggest that farmers understood and were able to benefit from our simple auction experiments. The results also suggest that a package auction, despite being more complicated to explain, performed better than a simple continuous double auction, both in terms of efficiency and in reducing risk. We see these results as an encouraging first step in a project to bring a centralized market to rural land trade in developing countries.

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