Can Market Design Help the World's Poor? Evidence from a Lab Experiment on Land Trade*

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Abstract

Market design has increased efficiency in complex reallocation problems in the developed world. Because reallocation may be necessary for development, there is potential for market design to contribute to reducing poverty. A key constraint is that low levels of literacy and numeracy may preclude the poor from benefiting from complex market designs. To understand the importance of this constraint, we conducted a lab-in-the-field experiment with Kenyan small-holder farmers. Farmers traded land in a hypothetical environment where theory suggests a package auction would thicken markets and reduce exposure risk. Comparing performance in a more complex package auction to a simpler continuous double auction we show that the added complexity increased efficiency, reducing the gap to the first best by around 26%. We find no evidence that the added complexity increased inequality.

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If resource misallocation plays an important role in keeping countries poor, then removing constraints to reallocation may speed the development process.[1] In many cases the logic of the Coase theorem is likely to hold, and enforcing property rights would allow decentralised markets to solve the problem. In other cases, however, the reallocation problem is highly complex and, even with perfect property rights, a decentralised market may not work. In these cases a more centralised approach is necessary (Milgrom 2017). The reallocation of agricultural land is a prime example. Many farmers owning an equal sized farm composed of many fragmented plots may be desirable in a setting with high risk, low mechanisation and no social security, but as a country develops it is necessary to defragment farms and reallocate them to the best farmers (Foster and Rosenzweig 2011, Restuccia 2016). But this process is highly complex. Each farmer must make many trades, bargaining with many different individuals, and early trades that are profitable for the traders involved can block efficiency in the market as a whole. All this in a setting with thin markets and holdup problems. Empirical evidence suggests that even with good property rights, decentralized land markets are slow to reach efficiency (Bleakley and Ferrie 2014).

Historically, complex reallocation problems have been controlled by the government. Under the Housing Act of 1930, the UK reallocated urban land from small scale informal housing to higher density formal housing through a series of "slum" clearance projects. Since the 1780's the Danish government has worked with local communities to defragment agricultural land under its land consolidation program (Hartvigsen 2014). Nearly all developed countries have operated similar programs in the past, and the FAO continues to apply these principles in many countries around the world. Before 1994, the US government allocated and reallocated spectrum through a system of "comparative hearings" (Roth 2002) . Between 1980 and 2000 the Indian government displaced between 16 and 40 million people as part of its dam construction projects, effectively reallocating these individual's homes and farms to the flood plain created (Duflo and Pande 2007). Starting in 2011, and continuing in to the future, the Tanzanian government plans to rescind the licenses of thousands of Daladala drivers (local bus drivers) transferring those rights to the operator of a new bust rapid transit system. Other examples abound.

More recently, and primarily in the developed world, it has become common to introduce carefully designed market incentives into complex reallocation problems (Kominers et al. 2017). Most famously, the reallocation of spectrum from TV to mobile telephony has been achieved in the US through the FCC's "incentive auction". These schemes introduce prices, allowing participants to express their preferences, and hence potentially improve

[1] See Hsieh and Klenow (2009) and the substantial literature that has followed

efficiency. However, they also shift some of the burden of complexity – for example the need to bid sensibly in the face of an extremely difficult reallocation problem with many constraints – from the government to the individual bidders.

We take a first step in understanding whether reallocation problems in developing countries can benefit from similar centralized market designs. We concentrate on what we believe to be a key constraint: if introducing market incentives transfers complexity from government to bidders, then low literacy and low numeracy individuals may struggle to understand the market and to participate effectively. This could lead to two separate kinds of problems. First, the market may fail to aggregate preferences, and hence not reach efficiency. Second, particularly if there is heterogeneity in understanding, the market may create inequality, and produce losers. The first problem would defeat the purpose of the market design, but the second is a particular concern, implementing a program that appears to attract trade and increase efficiency, but is in-fact reducing the welfare of poor and vulnerable people would be unacceptable. Hence the question we attempt to answer in this paper is: can the world's poor benefit from a market design approach, or does the complexity of market rules preclude efficiency gains or creates inequality?

To answer our question we ran a set of lab experiments in the field. We believe that a lab experimental approach is unavoidable for three reasons. First, and most importantly, concerns about inequality and possible negative effects mean that it would be inappropriate to field a large scale field experiment without first doing sufficient small scale experimentation. Second, there are a huge number of possible market designs, each with different properties and predicted to interact differently with details of local institutions. Small scale experimentation seems the only way to sort through these designs (Roth 2002). Third, on a more practical level, given that our chosen area is land trade, the appropriate unit of observation is the village or larger, and the number of participants would be enormous. A field trial of this size seems a bad first place to start.

We concentrate our efforts on an experimental version of the rural land trade problem for several reasons. First, the problem is of substantial interest in its own right. There is evidence that land is misallocated across farmers and operated at an inefficiently small scale (Foster and Rosenzweig 2011, Restuccia 2016), and there are currently a large number of government and FAO run land consolidation programs ongoing across the world. Second, as we noted above, the problem is complex, and so is likely to require a centralized solution. We believe the problem is one of the more complex problems likely to be faced during the development process, and so it is a good place to start. If small-holder farmers, a group with very low levels of education, are able to benefit from market design in one of the most complex settings, then we should feel happy that the a lack of participant understanding is likely to be minimal in other settings with less complex problems and more educated participants. Finally, the problem of land defragementation is familiar to millions of small-holder farmers across the developing world, so we have a large potential pool to work with.

We designed a simple representation of the land trade problem, involving 6 farmers in which there were gains from defragmenting land, and sorting higher performing farmers to higher quality land. Theory, which we discuss below, suggests that the land trade problem would benefit from a package auction design. We implemented three different market mechanisms based on the package market design of Goeree and Lindsay (2016).[2] In our first treatment, farmers were able to trade single plots of land in a continuous double auction, with a broker who facilitated communication (*CDA-Broker*). We consider this a low complexity benchmark. It is easy to understand, and mimics auction designs that many of our subjects were used to from local church auctions. Communication was allowed because exchange in Kenya is often done through direct bilateral bargaining and we are interested in market designs that can act alongside existing institutions. 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 conditional on selling (or buying) another plot (*CDA-Swap*). We allow cash to be offered or demanded as part of the swap. This is our intermediate complexity treatment. Our final treatment (*CDA-Package*) was the same as *CDA-Swap*, except that farmers could also make package offers, with a maximum of two buys and two sells. That is, they could offer to buy two plots, offer to sell two plots, and offer to sell (or buy) up to two plots conditional on buying (or selling) up to two plots. This is our highest complexity treatment, and in our context larger packages (for example sell 3 and buy 3) have no theoretical value as it is always optimal for each farmer to own exactly two plots.[3]

We use the CDA-Broker treatment as a benchmark and study the impact of adding complexity to the auction format. We show several results. First, the more complicated *CDA-Package* mechanism achieves higher efficiency. The CDA-Broker treatment enabled farmers to extract about 70% of the gains from trade, and the package treatment allowed them to incrase this by 8 percentage points or 26% of the remaining surplus. This shows

[2] The algorithm we use is near identical to the one in Goeree and Lindsay (2016) except that we impose XOR bidding whereas they use endogenous cash and holding constraints. Our stricter set of constraints is due to the complementarity that exists across plots of land; it ensures that a bidder doesn't defragment land with one winning bid and then break up their land holdings with another. Our designs also differ in that we allow communication in all treatments and use a different visualization scheme.

[3] We chose to constrain our package market following the principal that designs should be "as simple as possible, but not simpler." This aphorism is often attributed to Albert Einstein and is highlighted as a feature of good design by Bichler and Goeree (2017).

that our subjects are able to make use of a market design that one may conjecture is too complex. Second, we show that the gains from complexity are largely focused on the sorting of farmers. Across treatments, farmers extract most of the gains from defragmentation, but less of the gains from sorting. While CDA-Broker extracts about 15% of the gains from sorting *CDA-Package* improves on this by 10percentage points, extracting 75% more of the surplus or 11% of the remaining surplus.

Third, we show that farmers earnings are strongly correlated with their Shapley value, and that the complexity of the CDA-package treatment did not increase the deviation from the Shapely value, and may even have decreased it. We see this as evidence that complexity did not increase inequality, a key concern in our setting. From a theoretical perspective, exposure may lead to an asymmetric division of surplus, even if it does not create inefficiency.[4] To evaluate whether this occurs in our data we require a prediction for how surplus would be divided if bargaining was efficient and egalitarian; the Shapley value provides such a benchmark. We find a remarkably strong correlation between Shapley value and the ex-post division of surplus, regardless of treatment. This tight connection between behavior and the leading cooperative solution suggests that informal institutions may be important in our setting, and that interventions that can be overlaid atop these institutions may be particularly successful.[5]

Taken together, these results suggest small-holder farmers in Kenya can benefit from complex designs such as package exchanges and open the possibility of using these designs in a development context. We also show that formal market institutions can play an important role in improving land allocation. In the remainder of the paper we first discuss the land trade problem and why market design may have a role, before laying out our experimental design, then our results, before offering some final conclusions.

1 The Land Trade Problem

We argue that efficient trade requires *both* secure property rights *and* a careful design of the market mechanism, and we take some steps toward understanding the design problem. We take inspiration from Goeree and Lindsay (2016), who study a house reallocation problem. They propose, and experimentally verify, that a package market can help over-

[4]This is seen in Collins and Isaac (2012), who use a laboratory experiment to study a land assembly problem. Across their treatments surplus division is asymmetric: buyers receive only a small portion of the final surplus when trade is successful.

[5]A caveat is that the stakes in our experiment are much smaller than the value of land. If bargaining outcomes are supported by repeated game considerations, the temptation to deviate is likely to be much greater in real land auctions, and informal institutions may break down.

come an exposure problem that arises in two-sided settings that involve reallocation.[6] We adapt their approach, and demonstrate similar results in our setting: Kenyan farmers are able to understand and benefit from a package market despite its apparent complexity.

Formal empirical evidence 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 any) locations. Bleakley and Ferrie show that 80 years later, plot size correlates nearly one-to-one with the initial allocation, and that the correlation does not disappear until 150 years have passed. These results show two things: first, that the correlation eventually disappears implies that the initial allocation was not optimal; and second, that plot size persists shows that, even in the presence of strong property rights (the US), uncoordinated land trade is a very slow route to efficiency.

Anecdotal evidence from land consolidation programs also suggests that formal property rights are insufficient to allow consolidation. Throughout Europe, agriculture was, at some point, characterised by severe fragmentation.[7] At least since the 18th century, this fragmentation has been mitigated via government programs.[8] The Danish program is of particular interest. A group from the land office would work with a village for about 4 years to generate a plan for the reallocation of land.[9] After this, contracts of sale were drawn up and executed simultaneously and *voluntarily*. Figure 1 shows the change in land structure in one village. The change is striking in light of two observations: first, Denmark's institutions allowed free trade of land in the absence of the program; second, trade in the program was voluntary; hence every land owner weakly preferred the new allocation. These two facts imply that farmers wanted to defragment their land, but were unable to do so without a coordinating mechanism.

Theory also implies that uncoordinated land consolidation is difficult. First, given increasing returns at the plot level, uncoordinated land markets are likely to be thin because the most advantageous trades will be those that create contiguous plots, and so efficient trade is concentrated among neighbours. This thinness is predicted to impede trade in the presence of two-sided private information. Second, farmers who are proactive in de-

[6] As first explored in Goeree and Lindsay (2016), and explained more fully below, the exposure problem arises if a chain of trades that leads to an efficient outcome includes an negative surplus intermediate trade. We believe this to be one of several important constraints in our setting. A package market is one in which a trade can propose a set of trades. For example, a bidder can specify that she is willing to sell a specific plot if and only if she is able to buy a specific plot.

[7] Land is fragmented if farmers own multiple small noncontiguous plots.

[8] For a review see http://www.fao.org/docrep/006/Y4954E/Y4954E00.HTM

[9] See Hartvigsen (2014) for a review of the institutions used in Denmark.

fragmenting land may be subject to exposure risk. Suppose that it is optimal to hold two contiguous plots, and a farmer starts with two fragmented plots. Defragmentation requires two simple trades. If the first trade must take place at a loss and the second trade cannot be guaranteed to take place, perhaps because of holdout, then trading is risky and may not occur.[10] Finally, the efficient set of trades is likely to be complex. Efficient trades often involve multiple parties in a chain, and there are many possible trades and trading mechanisms that could be used.[11]

Theoretically, a centralized market design can mitigate these problems in a timely and apolitical manner.[12] In particular, a package exchange with XOR bidding[13] that allows for sufficiently complex packages: (i) increases market thickness by allowing farmers to bid on multiple consolidated farms independent of their initial allocation; (ii) removes the exposure problem by allowing all trades to take place at once; and (iii) reduces complexity, because both chains and trading rules are defined by the auction environment.[14] Packages may also relieve credit constrains as buying can be made conditional on selling.

A guiding principal of market design is that mechanisms work best when they are tailored to the needs of participants. A first step in designing a mechanism for rural land trade is to understand whether the target population – small holder farmers with little formal eduction – is able to trade efficiently using potentially complex market mechanisms.[15] Toward this aim, we designed a simple land trading environment, and implemented a framed field experiment in rural Kenya.

The environment has several features that mirror important aspects of the land trading

[10] Goeree and Lindsay (2016) is the first paper that we are aware of to point out this form of exposure in two-side reallocation problems. Exposure also arises in one-sided settings where objects are complements. See, for example, Rassenti et al. (1982), Brunner et al. (2010), Goeree and Holt (2010), and Chernomaz and Levin (2012) for package designs aimed at mitigating exposure in one-sided settings.

[11] An additional issue arises if there is asymmetric information about the quality of land. While we do not directly address this problem, we believe that it can be partially mitigated by initially exchanging leases (potentially with an option to buy) so that purchasing farmers have the ability to learn about land quality.

[12] 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.

[13] XOR denotes "exclusive or," i.e. participants can submit multiple bids simultaneously, at most one of which will be accepted.

[14] While there has been considerable recent work on package auctions, package exchanges have attracted much less attention. Combinatorial exchanges have been explored in the context of airport take-off and landing slots (Rassenti et al. 1982; Grether et al. 1989; Balakrishnan 2007), native vegetation offset permits (Nemes et al. 2008), pollution permits (Fine et al. 2017), housing (Goeree and Lindsay 2016) and the reallocation of spectrum (Milgrom and Segal 2017; Milgrom (2017)). For a review of the literature see Milgrom (2007) and Loertscher et al. (2015).

[15] Field evidence on the extent to which individuals in developing countries are able to trade efficiently in markets is mixed. See Bulte et al. (2013), Fiala (2015) and Haushofer and Zurlinden (2013) for experimental studies related to market efficiency in a developing country context.

problem. First, there are increasing returns at the plot level, so defragmenting land is efficient. Second, both farmers and land are heterogeneous in their productivity, and a complementarity means that efficiency is reached when high productivity farmers farm more productive land. We are thus able to study the ability of different market designs to achieve two goals: efficient land defragmentation; and efficient sorting of land. Third, there is a potential for exposure risk in our environment.

2 Experimental Design

2.1 Overview

We conducted 48 experimental 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, owned land, and were between 18 and 55 years of age. Approximately 70 per cent of invitees attended. Two initial pilots showed that females were more likely to attend, so males were oversampled, with a target invitation rate of 60% males.

At the beginning of each session, farmers were randomly assigned a computer and an enumerator, and read instructions in their preferred language (English, Swahili, or Gikuyu). The enumerator remained with his or her assigned farmer for the duration of the experiment, and also acted as a bid assistant.[16] After reading the instructions, the bid assistant's role was to answer any questions about the trading rules, calculate the surplus from any trade upon request, and input bids into the system. Enumerators also recorded earnings in each auction, and whether subjects communicated.[17] 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 auction in which they were encouraged to make bids using the mechanism assigned to their session. In the sessions that allowed for packages, enumerators encouraged their farmers to use all possible package structures and to make multiple bids.

Farmers then participated in 8 auctions, each lasting 10 minutes. As discussed in the

[16]Bid assistants are a common feature of real-life combinatorial auctions when the target population may have difficulty with the interface, and have been used, for instance, in the auction of slot machines and taxi medallions in Australia. To reduce the influence that an individual bid assistant might have on the experiment, we recruited extra bid assistants (16 total) and randomized bid assistants across treatments.

[17]In practice there was communication for all subjects in all sessions.

interface section, subjects could see their current allocation and bids on their screen, and a centralized screen showed the plots for which there were active bids. An additional enumerator was available in each session to act as a "broker." The broker would take oral messages between farmers, but was explicitly told not to actively organize trades.[18]

Farmers had a 30 minute break after the fourth auction, and were fed a light snack. At the end of the experiment, farmers were paid for all 8 auctions via mobile payment. The exchange rate was 20 points to 1 shilling. 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

Our environment was designed to study two issues: de-fragmentation; and farmer sorting. Fragmentation occurs if plots are not contiguous, and is conjectured to reduce efficiency. An effective market design should be able to de-fragment an allocation, and allow land to flow to the most productive farmer, leading to efficient sorting.

In each session, 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 were three land types: blue land was the most productive, red the second most and green the least. Second, there were three farmer types: high productivity, medium productivity and low productivity. In all sessions there were two of each type of farmer. Panel A of Figure 3, shows total profit for each farmer and land combination. A high productivity farmer always earned twice as much as a low productivity farmer, and a medium productivity farmer earned one and a half times as much. Red land was twice as productive as green land, and blue land was one and a half times as productive. This setup creates a complementarity. For example, the gain from moving from green to blue land was 200 for a high type, but only 100 for a low type. Hence, efficiency required the high type farmers to farm the blue land, the medium type farmers to farm the red land, and the low type farmers to farm the green land.

There was also a bonus for operating adjacent plots, and a cost from operating too many plots. A farmer who operated two adjacent plots of the same colour received a 20% bonus, as shown in Panel B of Figure 3. A farmer who operated more than two

[18] 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.

plots, earned only the profits of the two most profitable. The adjacency bonus allows for an increase in productivity from de-fragmentation. The complementarity allows us to study sorting. The fact that a third plot is not productive allows us to introduce a complementarity, but avoid a situation in which efficiency requires all land to be held by the most productive farmer. It also allows us to introduce exposure risk with a simple to explain production function. We explained the two-plot restriction as a 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 and that there were three types of farmers. However, details of the other two production functions, and the assignment of types to subjects, was not revealed. Subjects knew which plots were owned by which subjects.

2.2.2 The Initial Allocation of Land

We conjectured that the the initial allocation of plots would affect the ease of achieving defragmentation and efficient sorting. To study this issue, we created eight different initial land allocations, which are shown in Figure 4. In each map, players 1 & 2 are high types, players 3 & 4 are medium types and players 5 & 6 are low types. The maps are symmetric within player type. That is, players 1 & 2 are interchangeable, players 3 & 4 are interchangeable, and players 5 & 6 are interchangeable.

The allocations are ordered according to our pre-experimental assessment of how difficult it would be to reach full efficiency. We considered four dimensions of difficulty. First, for each player, we determined how many *CDA-Broker* trades were necessary to get to their efficient allocation.[19] Second, we considered how many farmers would need to be involved in any efficient *CDA-Swap* trade. Third, we considered whether money was required to reach an efficient outcome. Finally, we considered strategic issues, for example the extent to which one farmer could holdup another farmer.

Map 1 was thought to be the simplest. For each player, reaching efficiency requires only one *CDA-Swap*, and only two participants are involved in each trade. No money is required, because all efficient trades increase all participants' surpluses equally. Map 2 is similar to Map 1, but money is required because efficient trade reduced land value for some farmers. For example, players 1 and 3 must swap land, but this will reduce farmer 3's output and so she must be compensated. Map 3 is similar to Map 1, and in principle requires no money. However, players 2, 4 and 6 might have a strategic motive to holdout and exploit the weak bargaining positions of players 1, 3, and 5. Map 4 can be solved

[19] Note that if an allocation required two *CDA-Broker* trades, it required only one *CDA-Swap* trade. If an allocation requires four *CDA-Broker* trades, it requires two *CDA-Swap* trades or one *CDA-Package* trade.

with only one *CDA-Swap* per player, but those trades require a chain of 3 participants. Money is required, but there is no strategic issue. Map 5 was thought to be more complex than Map 4, and requires two *CDA-Swap* trades or one *CDA-Package* trade by each player to reach the efficient allocation. Each of those trades involves only two players, money is required and there does not appear to be a strategic issue. Map 6 again requires two *CDA-Swap* trades, but in this case, some of those trades require a 3 person chain. Again, money is required and their does is not obvious strategic issue. Map 7 is similar to Map 6 but appears to have a holdout problem; player 6, for example, may not wish to sell. Finally, we judged map 8 to be the most difficult. It requires two *CDA-Swap* trades per player and some of those trades require a chain of 4 players.

It should be noted that in coming to our ex-ante assessment 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 in Section 3.4.

In ranking initial allocations, our goal was to generated a variety of maps and allow empirical evaluation the conjecture that initial allocation matters. We show below that initial allocations do matter, and believe that there may be interesting work to do in formalizing the intuitions presented in this section.

2.2.3 Trading Mechanisms

We consider three trading mechanisms based on the continuous double auction and the package market of Goeree and Lindsay (2016): 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 package orders consisting of one sale and one purchase, and a *CDA-Package* mechanism where subjects can place buy orders of up to two units, sell orders of up to two units, and package orders consisting of up to two buy orders and up to two sell orders. Communication through the broker is available in all three mechanisms.

Winner determination and surplus division are as outlined in Goeree and Lindsay (2016) with some modifications to impose XOR bidding. 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 trying 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 $(-500, \langle 1, 0, ..., 0 \rangle)$ indicates that a farmer is willing to pay up to 500 points to acquire plot

1, while an order $(0, \langle 1, -1, 0, ..., 0\rangle)$ 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 $\omega_i^t + x$ contains only zeros and ones. 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 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 offered is not positive. Formally, let $\mathbb{O}^t$ denote 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 $V^* \geq 0$.[20]

When a transaction is triggered, we return plots that were not demanded 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 farm-

[20]Note that the restriction to 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 required to solve the winner allocation problem, and to make farmers aware of attempted bids that could not be exercised. Relative to Goeree and Lindsay (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. Further, we only use the bids of non-winners to set prices, while Goeree and Lindsay (2016) use all non-winning bids. This change avoids a situation that can arise in our setting, where bidders impose revealed preference constraints on themselves, and reduce their own surplus.

ers. 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 $s_j(p) = -m_j - p \cdot x_j$.[21] 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 constraints of the losing orders.[22] The revealed preference constraints ensure that a losing farmer would not prefer to have won once the surplus is reallocated given the information that was submitted to the market. 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 pay and receive nothing. In the case of ties, we use the first solution found by the solver.[23]

As can be seen in 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

[21] 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 trading in Kenya Shillings on a day-to-day basis.

[22] See Kwasnica et al. (2005) for a broader discussion of revealed preference constraints.

[23] The underlying algorithms were written in Minizinc, a free open-source constraint modelling language, and solved using GECODE (Nethercote et al. 2007; Stuckey et al. 2014). 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 under 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 problems that occur if prices aren't fully pinned down by orders. In practice, the timeouts were never triggered.

and a single sell order and where the non-winning buy order pins down prices.

After a transaction is triggered, all non-winning orders made by farmers in the winning coalition become inactive, and we allow farmers to renew any legal orders if they wish. Orders that are made illegal (for instance, orders that contain sale offers 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 withdraw legal orders at any time.

2.2.4 Interfaces

All bids were entered through a computer interface. The interface displayed the farmer's valuations and current allocation on a geospatial map as in Panel (a) of Figure 2, and provided a calculator that could be used to determine 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 the farmer. In addition to the individual interfaces, a projector showed a map which indicated who owned each plot of land and when a plot of land was offered for sale, or had an offer to purchase. Combinatorial bids showed up on the projected interface as separate components. A screenshot of the individual and projected interfaces is shown in Figure 5.

2.2.5 Cash Constraints and Exposure Risk

Exposure risk exists if reaching an efficient allocation requires at least one farmer to make a loss on an intermediate trade. This may discourage all trade if future transactions that compensate for the loss cannot be committed to. In practice, subsequent trades may not occur, either because of strategic holdup, or because of changes of circumstance.

To see that intermediate trades may lead to losses, consider a situation with initial allocation

3	4			blue lots
3	1	1	4	red lots,

and the efficient allocation

1	1			blue lots
3	3	4	4	red lots.

Initially the land values are 720, 525 and 525 for 1, 3 and 4 respectively; after trade they are 960, 540 and 540. Thus, there exists a sequence of trades that is mutually beneficial. Getting to efficiency, however, requires intermediate trades that create losses. If 1 first buys from 3, he holds three plots and cannot farm them all. After this intermediate trade his landholding is still worth 720, while farmer 3's value has decreased to 225. Since the surplus from this trade is negative (-300), someone must make a loss. Alternatively, 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 again someone must make a loss.

There are three reasons why simple trades (i.e. a sale and purchase of one plot) may have negative surplus in our setting. First, as in the example, a purchased plot may not be farmed, because the buyer now has three plots. In this case output is lost until the buyer sells a plot. Second, the buyer may produce less from the purchased plot than the seller, because of type productivity differences. This would occur, for example, when a high type farmer owns low type land. Efficiency requires that this land be sold to a low type farmer, and that the high type farmer later acquire high type land. But, the initial sale reduces total output. Third, the trade might break up a previously consolidated set of plots. This would occur, for example, if a high type farmer owned two adjacent medium type plots. Efficiency requires that the high type farmer sell these plots and acquire high type plots. Any simple trade would require first that the adjacency bonus be lost.

We introduced an additional experimental feature, cash constraints, to increase the likelihood that trade creates exposure risk. In half of all auctions, farmers started with cash of 750. This is enough money to induce any farmer to sell any single plot. In particular, it would be sufficient to compensate a high productivity farmer with two adjacent high quality plots for selling one.[24] In the other half, the cash endowment was 250. This is not enough to compensate all farmers for all efficiency increasing simple trades. For example, efficiency requires a medium type farmer who owns two consolidated high quality plots to sell to a high type farmer. This trade reduces the medium types output by 460. With only 250 in cash, the high type farmer cannot fully compensate the medium type farmer for this loss in output.

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

[24] The land value before a sale is 960. after a sale his land value would be 400. Thus, the difference is 560. If this farmer were offered 750 to make this trade she would be willing.

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. Each of the 6 treatments was then randomly assigned to one of the sessions within each block.

Each lab session required one lead enumerator to introduce the environment and implement the computer programs, 6 bidding assistants, 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 farmer and lab (e.g. farmer 4 red) on a session by session basis. Brokers were also randomly assigned on a session by session basis.

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 farmer played four auctions as their initial player number, and was then moved to a different player number. This was done such 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. To assign orders to sessions, we first randomly permuted the 8 map orders as shown in Figure 6. We then assigned map orders 1 to 6 to the sessions in block 1 (in order), orders 2 to 7 to block 2 (in order), etc.

Overall, this method gives assignment to the main auction 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 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 one plot on average. 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 had ever 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 interface, 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, our lead enumerators raised concerns that the other enumerators did not fully understand the rules of the more complicated package exchanges. These concerns diminished as the experiment progressed. As the enumerators were responsible for translating the instructions and teaching farmers, it is likely that farmers did not fully understand the mechanisms in the early sessions. Looking at the data, the first two sessions in each treatment accounted for 43% of auctions where efficiency was in the bottom decile, and accounted for 63% of auctions where efficiency was negative. Figures 7a and 7b show the evolution of efficiency overtime, broken down by treatment.[25] 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 treatments difficult to explain. Figure 7b is the same as Figure 7a but a linear fit is added to the data after block one. This figure shows that, after removing block one, learning is even across the three treatments.

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. Third, in our preferred specification, we also include a linear time trend. In all specifications we 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. Summary figures

[25] Efficiency is formally defined below.

quoted in-text are from our preferred specification.

We lost one session due to the accidental reformatting of the server computers.[26] We also drop one session where the wrong mechanism was used, and two auctions where the wrong configuration was used. In total our data consists of 46 sessions, 366 auctions, 276 farmers, and 2196 farmer-auction observations.

3.2 Efficiency

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

$$\text{Efficiency} = \frac{\sum_{i=1}^{n} \left(s_i^{final} - s_i^{initial} \right)}{\sum_{i=1}^{n} \left(s_i^{optimal} - s_i^{initial} \right)}, \tag{1}$$

where s_i^{final} is final surplus generated by farmer i, $s_i^{initial}$ is farmer i's initial surplus, and $s_i^{optimal}$ is the surplus farmer i would generated at the optimum. Efficiencies are bounded above by 1, and are the proportion of possible gains realized in a given auction.

Result 1 *Average efficiency is 70 percent or higher. The* CDA-Package *mechanism achieves 8 percentage points more efficiency than the* CDA-Broker *mechanism.*

Support for Result 1 is given in Figure 8a and Table 2. Figure 8a shows average efficiency and 95% confidence intervals, for each of the three market mechanisms. As can be seen, average efficiency is high under all three mechanisms, with an average efficiency rate 70% or higher in all treatments.

The *CDA-Broker* mechanism has the lowest average efficiency of 70%. This efficiency is high relative to the work of Goeree and Lindsay (2016) who document poor performance of a CDA in a house auction with exposure risk. As indicated in the introduction, a major difference in our designs is that we allow for communication through a broker, potentially allowing farmers to mitigate exposure risk through informal agreements.[27]

To see how communication influenced trade, we look at the transaction level data. In our pilots, deals negotiated through the broker typically led to simultaneous buy and sell bids at the arranged price. Such bids register in the system as having no surplus to divide

[26] 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.

[27] We also had a different value structure and use a shared graphical visualization of open trades.

(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 high proportion of trades are brokered, and that the proportion of brokered transactions declines as the available package size grows. 37% of transactions in the *CDA-Broker* treatment are brokered, while brokered transactions account for 20% of transactions in the *CDA-Swap* mechanism, and just 16% of transactions in the *CDA-Package* auctions. All these differences are significant in an OLS regression with errors clustered at the session level (p-value $< .01$ for all comparisons). Our data thus suggests partial substitution between communication and formal package mechanisms.

Table 2 reports coefficients from an OLS regression with efficiency on the left hand side, and the mechanisms on the right. *CDA-Broker* is the left out. Our preferred specification is (5), which controls for block fixed effects and time trends, and leaves out the first block, as discussed above. In this specification, the *CDA-Package* mechanism has significantly higher efficiency than the *CDA-Broker* mechanism. From a base of 70% efficiency, the *CDA-Package* mechanism increases efficiency by 8 percentage points, or 11%. Efficiency is 4 percentage points (6%) higher in *CDA-Swap* than *CDA-Broker*, but the difference is not significant.

As discussed above, we also changed the amount of cash that farmers started with. This was designed to alter the degree of exposure risk. Regardless of the specification, the low-cash treatment does not statistically significantly alter efficiency, and this lack of impact does not depend on the treatment. This results suggest that farmers were able to deal effectively with the greater exposure risk that comes from a tighter cash constraint, although it should be noted that we have low power to detect interaction effects.

3.3 Fragmentation and Sorting

We next ask how the different treatments performed at the two separate tasks of defragmentation and sorting. For a given allocation of land, let y_i denote the value associated with farmer i's two best plots (ignoring consolidation bonuses), and let $c_i \in \{0, 1\}$ indicate whether these plots are fragmented ($c_i = 0$) or consolidated ($c_i = 1$). Based on the production function used in the experiment, it follows that the total profit on farmer i's land is $s_i := (1 + 0.2c_i)y_i$. After some algebra, the change in surplus from a farmer's initial allocation to their final allocation can be rewritten as:

$$s_i^{final} - s_i^{initial} = \underbrace{0.2\left[c_i^{final} - c_i^{initial}\right] y_i^{initial}}_{\text{Defragmentation}} + \underbrace{\left(1 + 0.2c_i^{final}\right)\left[y_i^{final} - y_i^{initial}\right]}_{Sorting}.$$

We interpret the first term as the change in surplus due to defragmentation and the second term as the change in surplus due to sorting.[28] Aggregating over the six farmers, and normalizing by the maximum change in social surplus, we calculate a defragmentation and sorting measure for each auction:

$$\begin{aligned} \text{Defragmentation}^{abs} &= \frac{\sum_{i=1}^{n} 0.2\left[c_i^{final} - c_i^{initial}\right] y_i^{initial}}{\sum_{i=1}^{n}\left[s_i^{optimal} - s_i^{initial}\right]} \\ \text{Sorting}^{abs} &= \frac{\sum_{i=1}^{n}\left(1 + 0.2c_i^{final}\right)\left[y_i^{final} - y_i^{initial}\right]}{\sum_{i=1}^{n}\left[s_i^{optimal} - s_i^{initial}\right]}. \end{aligned}$$

Note that, by construction, Efficiency $=$ Defragmentation^{abs} $+$ Sorting^{abs}.

Figure 9 shows these measures, first for a hypothetical case where full efficiency occurs in each auction, and then for each of the three treatments. Looking first at the full efficiency case, note that defragmentation accounts for 73 percent of the available gains, while sorting accounts for only 27 percent. The lower potential gain from sorting is due to our selection of initial allocations: two of our easiest maps (Map 1 and Map 3) had no gains from sorting, while two of the remaining maps (Map 2 and Map 4) had only small gains. The figure shows that farmers were able to capture most of the available gains from defragmentation, and this does not depend on the auction format. In contrast, farmers extracted only a small percentage of the available gains from sorting, and the *CDA-Package* treatment performed significantly better in this regard.

To further understand defragmentation and sorting rates across the treatments, we renormalize our defragmentation and sorting measures so that they are bounded above by

[28] Due to the multiplicative nature of the adjacency bonus, a farmer who both consolidates land and sorts to higher quality land will get a larger adjacency bonus then one who retains her lower quality land. This implies that there is not a perfect separation between the gains from defragmentation and the gains from sorting. The decomposition we have chosen holds the quality of land fixed at the initial allocation for the purpose of calculating defragmentation and assigns the additional gains and losses to sorting. The results in the analysis below are robust to alternative decompositions and to specifications that count the number of fragmented lots rather than weighting them by their value.

one. For defragmentation, we calculate:

$$\text{Defragmentation} = \frac{\sum_{i=1}^{N} 0.2 \left[c_i^{final} - c_i^{initial}\right] y_i^{initial}}{\sum_{i=1}^{N} 0.2 \left[1 - c_i^{initial}\right] y_i^{initial}}, \tag{2}$$

and for sorting, we calculate:

$$\text{Sorting} = \frac{\sum_{i=1}^{N} \left(1 + 0.2 c_i^{final}\right) \left[y_i^{final} - y_i^{initial}\right]}{\sum_{i=1}^{N} (1 + 0.2) \left[y_i^{optimal} - y_i^{initial}\right]}. \tag{3}$$

Note that the sorting measure is not defined in Maps 1 and 3 because all farmers start with their efficient land types. We thus drop these observations.

Result 2 *Defragmentation rates are over 80% in all three auction formats, with no statistically significant difference between treatments. The treatments are less successful overall at improving sorting. The* CDA-Broker *treatment realizes only 35% of potential gains from sorting. However, the* CDA-Package *treatment improved sorting by 16 percentage points (48%) in our preferred specification.* CDA-Swap *improved sorting by 4 percentage points (not significant).*

Table 3 reports the impact of our treatments on defragmentation. The defragmentation rate is surprisingly high in the *CDA-broker* treatment, suggesting that subjects are effective at agglomerating land, even in mechanisms that do not allow for packages. Somewhat surprisingly, the *CDA-Swap* mechanism has a similar defragmentation rate. The *CDA-Package* auction achieves slightly more defragmentation than the other two treatments, but the differences are not statistically significant.

Table 4 reports the treatment effects for sorting. As can be seen from the control group means, the *CDA-Broker* mechanism improved sorting by only 35% of the optimum.[29] Relative to this, there is evidence (column 5) that *CDA-Package* improved sorting by 16 percentage points.

[29]There are a number of reasons why defragmentation may be easier for farmers to accomplish then efficient reallocation. First, from the standpoint of mechanism design, defragmentation shares similarities with the partnership dissolution problem of Cramton et al. (1987) in the sense that both parties in a swap act as both a buyer and a seller and own a "share" of the efficient allocation. In such settings (and in contrast to the bilateral trading setting of Myerson and Satterthwaite (1983)) it is often possible to induce efficient trade without generating a budget deficit (Loertscher and Waser 2017). Second, empirically, farmers often worked towards defragmenting land first and then tried to move to more efficient lots. This ordering of transactions may have exacerbated the exposure problem in the *CDA-Broker* and *CDA-Swap* formats, since farmers had to break up contiguous blocks as part of any move. Finally, two of our easiest maps (maps 1 and 3) began optimally sorted. This implies that only the harder set of maps are used to determine the improvement in sorting.

Taken together, our efficiency, fragmentation, and sorting results suggest that there *CDA-Package* performs better than the other formats, driven by improved sorting. Relative to earlier studies, the difference in efficiency across our three mechanisms is small, suggesting that communication and informal agreements are an imperfect substitute for packages. Looking deeper at the transaction level data, it appears that farmers substitute away from brokered trades and toward trades that utilize the centralized system when they are given the ability to construct packages.

3.4 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 perceived difficulty. Figure 10 shows efficiency, defragmentation, and sorting, 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 initial allocation is important for determining the level of efficiency. In each case, the F-statistic implies that there are significant differences across the maps. However, it is not the case that efficiency achieved is monotonically decreasing, as we had anticipated. In retrospect, we ranked maps by a conjecture on whether or not *full* efficiency would be reached. As shown above, however, full efficiency was rarely reached, and so ease of reaching partial efficiency was more important. For example, on the basis of full efficiency, we believed that Map 8 was very hard, and Map 5 less difficult. Inspection of Figure 10a, however, implies that this was not the case. Figures 10b and 10c give some idea as to why this is the case, Map 8 was easy to defragment, but Map 5 was not. With hindsight this seems predictable, Map 8 seems easy to defragment, but hard to fully sort.[30] 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.

[30] 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 improve sorting, but 5 is hard to defragment.

3.5 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. We also found little evidence that credit constraints influence efficiency, which suggests that farmers found alternative ways to mitigate exposure risk. In this section we study the division of surplus between participants, and show further evidence that subjects use communication and informal institutions to reach agreements that are both egalitarian and efficient.

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. Such sequential trade naturally leads to hold up, which reduces returns from making initial transactions. If the holdout problem is severe, farmers may fear expropriation leading to trade frictions and inefficient allocations. However, when holdout is less severe, some farmers may still be willing to make initial trades, as long as the expected profit of completing a chain of trades is positive. In these cases, exposure should generate variation in the division of surplus, rather than reducing efficiency. This is a particularly important issue for us. A real world land market would involve potentially vulnerable individuals, and a mechanism that increases inequality, or some how favours more able traders, would not be acceptable.

Our environment is one where farmers are heterogeneous in their initial bargaining positions, being assigned different land and different productivity types. Thus, even if farmers are not taking advantage of their strategic position, we would naturally expect to see variation in outcomes. To control for this natural variation, we turn to cooperative game theory. Recall that in cooperative models of bargaining, coalitions bargain to the Pareto frontier, and 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. A remarkable result in cooperative game theory, shown in Shapley (1953), is that there is a unique division of surplus that arises under the "egalitarian" axioms of symmetry, efficiency, linearity, and invariance to dummy players. We use the Shapley values as a benchmark; they are the outcomes we would expect if farmers receive an equitable share of the surplus.

In our environment, 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 farmer i, is given by

$$\phi_i(v) = \sum_{S \subseteq \mathbb{F} \setminus \{i\}} \frac{|S|!(6 - |S| - 1)!}{6!} (v(S \cup \{i\}) - v(S)), \tag{4}$$

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, and is a natural generalization of marginal contribution in this setting. By construction $\sum_i \phi_i(v)$ add up to the value of the grand coalition, V^*.

We construct the Shapley value for every individual, and every auction, excluding the cash that the players is given at the beginning of the game. The Shapley value assumes that participants will reach efficiency, which is not the case in most auctions. 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 farmer is the same as that suggested by the Shapley value, even away from the Pareto frontier. We compare this to the surplus that the farmer earned in the experiment, excluding the cash that the farmer was given at the beginning of the game.

Result 4 *The scaled Shapley value is a strong predictor of the shares received by farmers in all three mechanisms. There is weak evidence that there is a reduction in the variance of the distribution of surplus in the* CDA-Package *treatment.*

Evidence for this result is shown in Figure 11 and Table 5. As can be seen in Figure 11 there is a near one-to-one relationship between the scaled Shapley value and the surplus a farmer receives in the auction. In Table 5, the odd numbered columns show regressions with surplus as the left hand side variable, and the scaled Shapley value as the explanatory variable. As above, our preferred specification (column 7) drops the first block and includes block fixed effects, trends, and gender and lab controls. The results are quite striking. First, the coefficient on the scaled Shapley value is almost exactly 1, and the intercept is very precisely estimates to be zero (in column 1, which excludes the fixed effects), suggesting that on average the scaled 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 scaled Shapley value.

In the even columns of 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 in *CDA-Package* are around 30% lower than in *CDA-Broker*, though the effect is marginally significant, and only in one specification.

While the original intent of constructing the Shapley value was to assess the impact of exposure and holdout on the division of surplus, the relationship between the Shapley value and surplus is striking and one may wonder the extent to which the relationship reflects a mechanical connection between initial values and final surpluses. To see the issue, consider a world with only two farmers who each own a single piece of land and who value their own piece of land at values v_1 and v_2. If, by swapping the land, they would receive a joint surplus of $S > v_1 + v_2$, the Shapley value for farmer 1 would be given by $\phi_1 = v_1 + (S - v_1 - v_2)$ and the Shapley value for farmer 2 would be given by $\phi_2 = v_2 + (S - v_1 - v_2)/2$. By construction, ϕ_i is positively correlated with the original allocation, and this correlation becomes stronger as $(S - v_1 - v_2)/2$ grows small. This may lead to a mechanical relationship, where non-trading farmers closely match their Shapley Value in auctions where the returns to trade are small.

To eliminate the mechanical relationship, we calculate $\hat{\phi}_1 = \phi_1 - v_1$ and compare it to the difference between a farmer's final surplus and his initial allocation. Figure 12 shows this relationship for all farmers and all auctions.[31] While the relationship is less tight than the original Shapley Values, the R^2 remains high, and the slope term of .88 is remarkably close to the theoretical prediction of 1. Note also, there are very few cases where the change in surplus is negative, implying it is rare for a farmer to lose money by participating in an auction. Overall, only 4.4% of auction-farmer pairs end in a loss, and all but 1.8% of farmers increased their surplus relative to their initial endowments across all 8 auctions.

The experimental bargaining literature has focused primarily on two-person and three-person bargaining games, and typically finds that pairs tend to split surplus more evenly than is predicted by the Shapley value.[32] In our experiment, we find no tendency towards more equal surplus division. This may be due to the market environment in which participants are trading, and the pricing mechanism, which uses bids placed by non-winning participants as revealed preference constraints. Farmers in our environment may also be accustomed to bargaining in asymmetric environments, and may view variation in outside options as natural constraints in the division of surplus.

Overall, our results suggest that farmers bargain quite effectively as a group, and that

[31] There are 7 observations with net profit below -200 that are not shown in the graph.

[32] For surveys in bargaining see Roth (1995) and Camerer (2003). See also Anbarci and Feltovich (2013) for an experiment related to variation in disagreement payoffs and de Clippel and Rozen (2013) for structural estimation of bargaining models in three-player bargaining games.

bargaining is influenced by position in ways that is consistent with the Shapley value. In addition to increasing efficiency, there is weak evidence that our *CDA-Package* treatment reduces strategic risk, suggesting that the introduction of packages may reduce hold-out in realized trades, in addition to facilitating efficiency improvements.

4 Conclusion

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. To help understand how market design might be used to improve the land allocation, we implemented a framed field experiment in rural Kenya, where we study the performance of a range of two-sided market designs. Our results suggest that farmers understood the mechanisms and were able to benefit from the auctions. Our results further suggest that a continuous-time package exchange tailored from the package market of Goeree and Lindsay (2016) performed better than a simple continuous double auction, both in terms of efficiency and in reducing variation in payoffs. The gains over other mechanisms appear to come primarily from improving the allocation of farmers to plots. We see these results as an encouraging first step in a project to bring centralized markets to rural land trade in developing countries.

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Figures

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

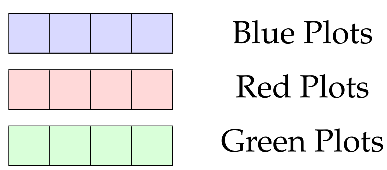


Figure 2: Map Representation of Available Land

		Panel A: Profits			Panel B: Adjacency Bonus		
		Land Type			Land Type		
		Blue	Red	Green	Blue	Red	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

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

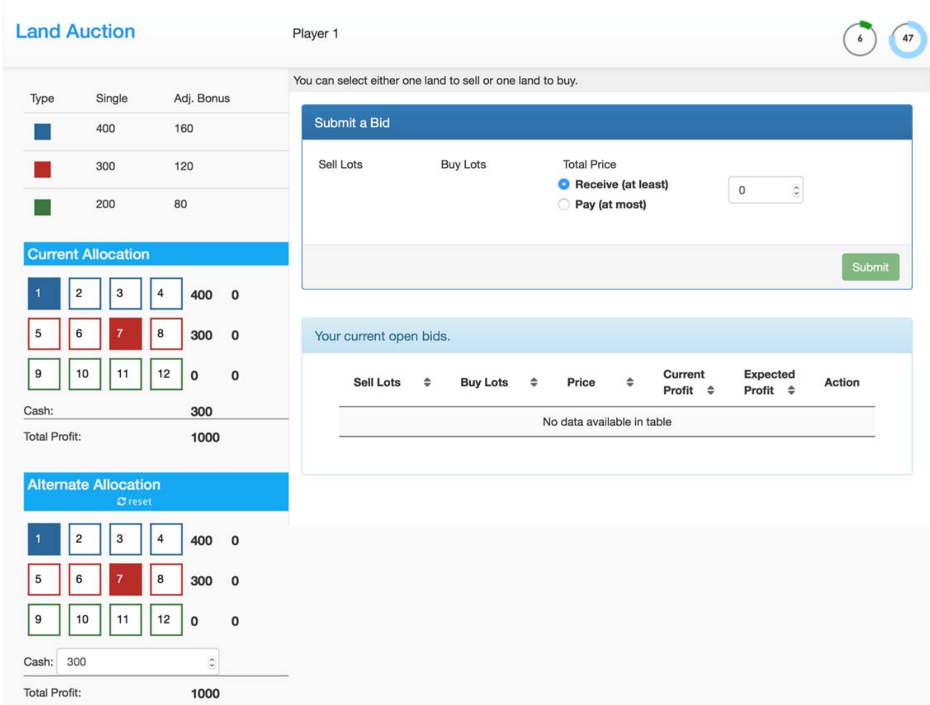
Map 7

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

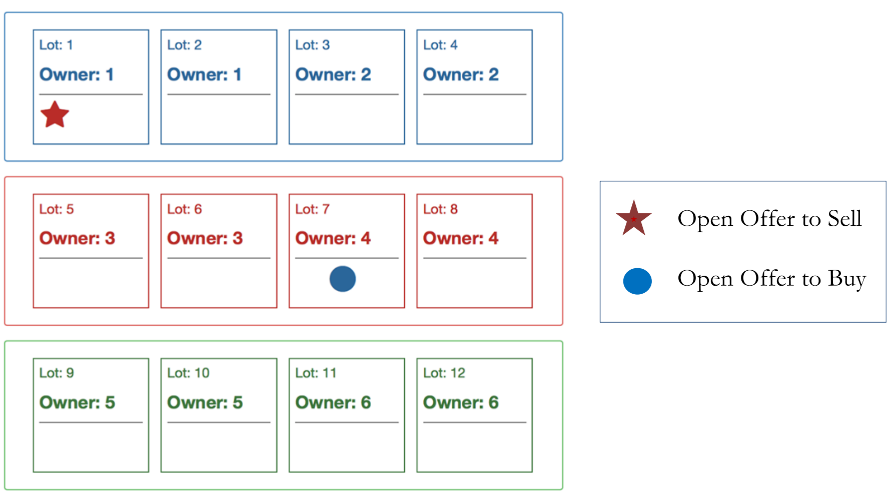
Map 8

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



Panel (a): Computer Interface Used by Farmers

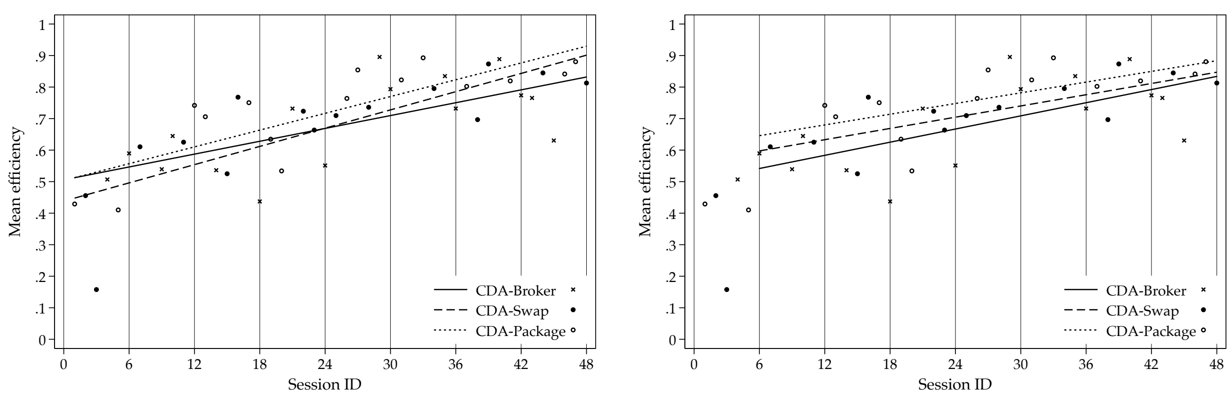


Panel (b): Projected Land Market Interface

Figure 5: Computer Interfaces

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

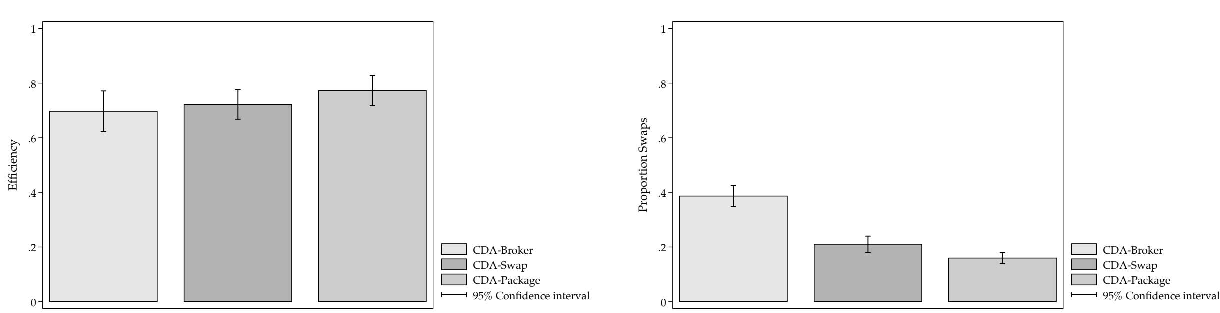
Figure 6: Map Orders



(a) Linear fit including all Blocks

(b) Linear fit excluding Block 1

Figure 7: Mean Efficiency by Experimental Session



(a) Efficiency by Treatment

(b) Brokerage by Treatment

Figure 8: Efficiency and Brokerage levels Across Treatments

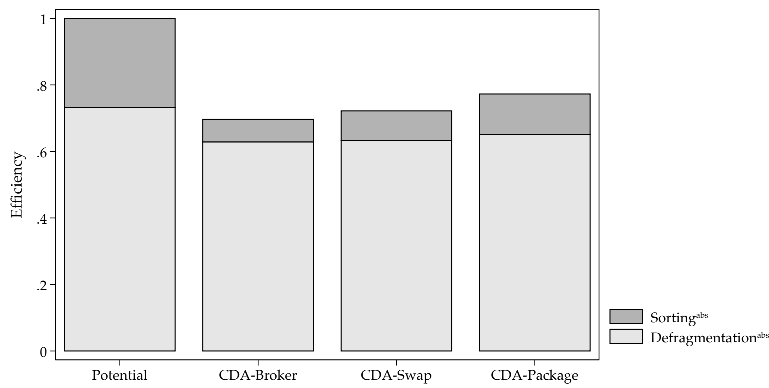
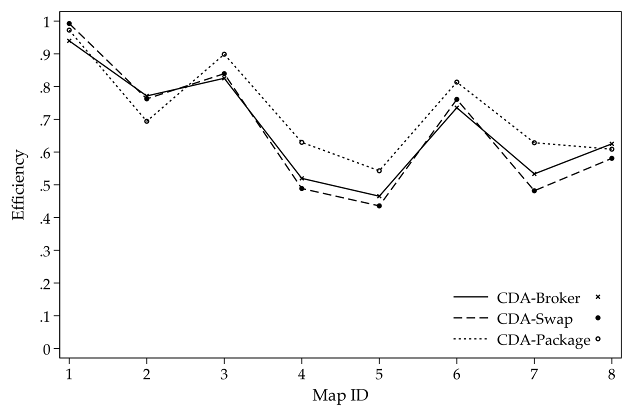
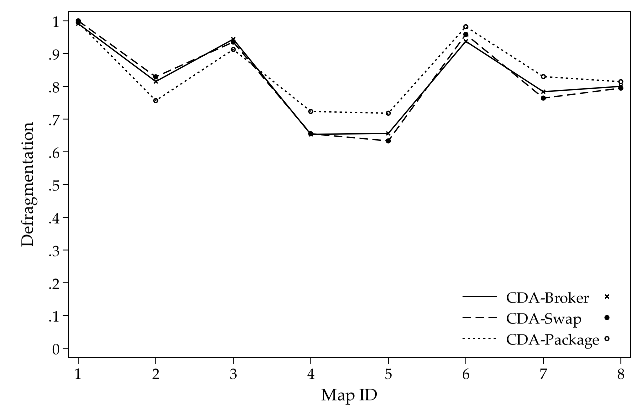


Figure 9: Efficiency decomposition



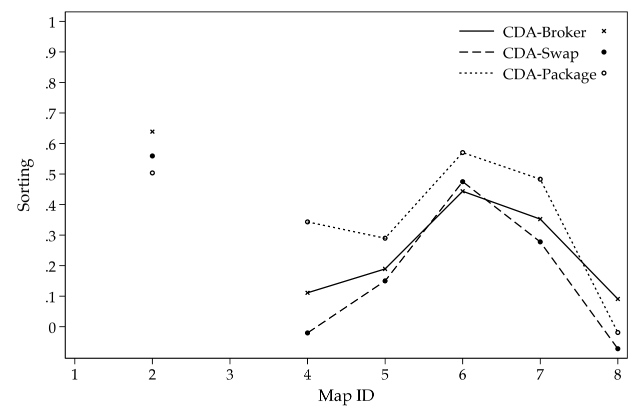
F-test for no difference by map: $F(7,45) = 27.93$, $p < 0.01$.

(a) Mean Efficiency



F-test for no difference by map: $F(7,45) = 30.78$, $p < 0.01$.

(b) Mean defragmentation



F-test for no difference by map: $F(5,45) = 16.70$, $p < 0.01$.
Note: measure not defined for maps 1 and 3.

(c) Mean improvement in sorting

Figure 10: Efficiency, Defragmentation and Sorting by Initial Allocation

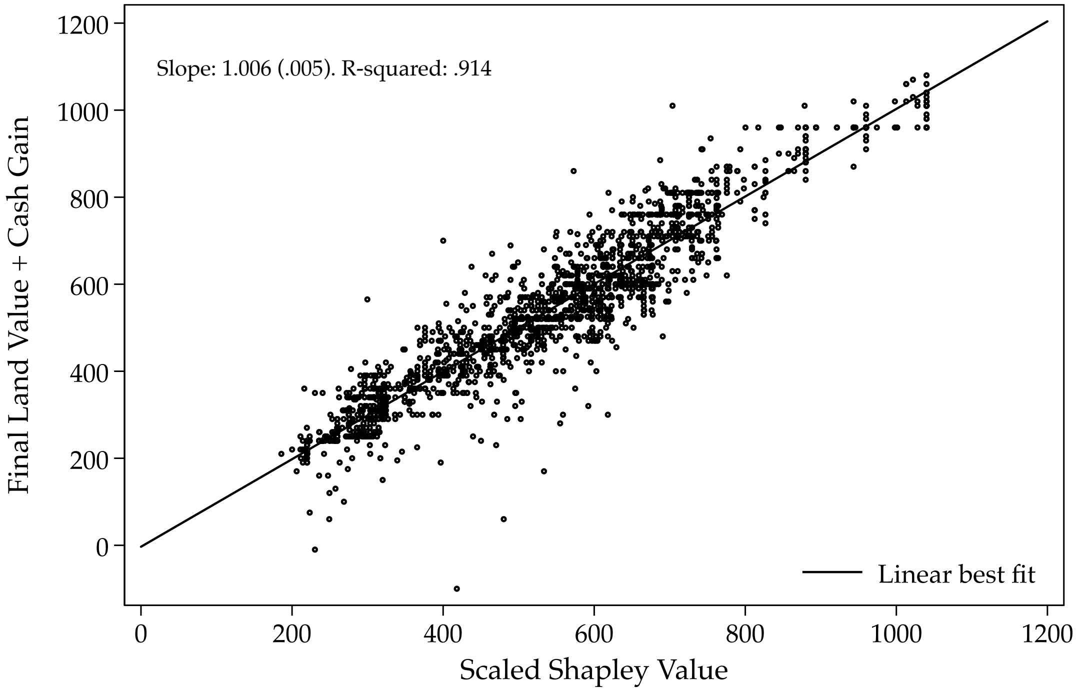


Figure 11: Scaled Shapley Values Predict Profit

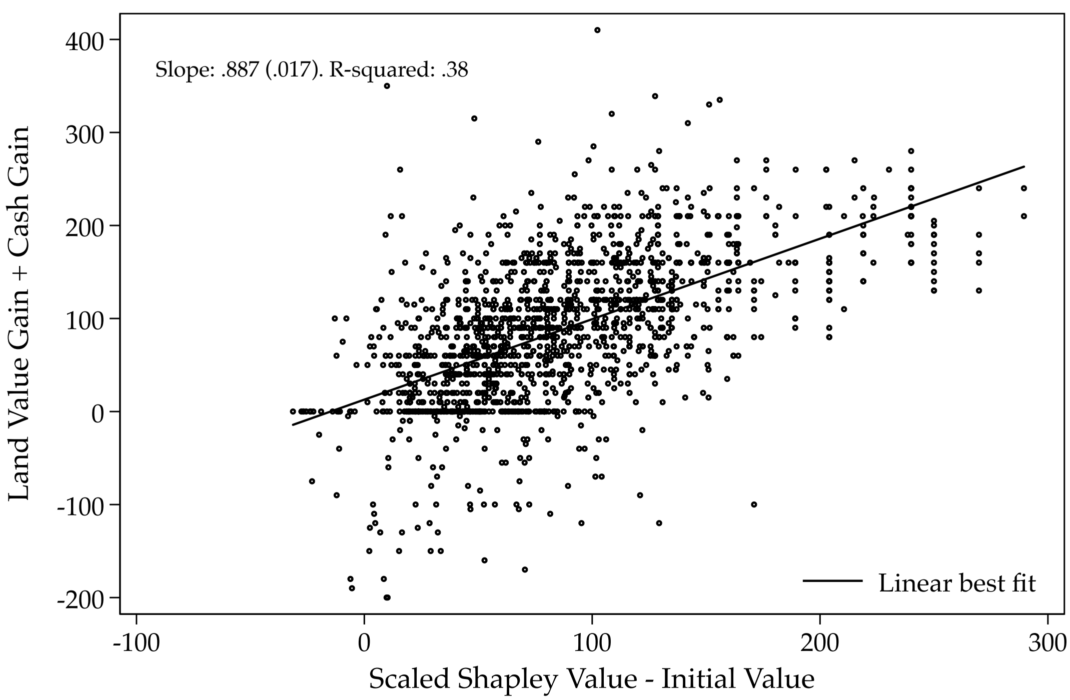


Figure 12: Scaled Shapley Values Predict Profit

Tables

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	42.91	43.29	41.48	42.56
	(11.32)	(9.324)	(10.27)	(10.38)
Education (years)	9.578	9.628	10.65	9.945
	(3.426)	(3.026)	(3.190)	(3.260)
Married	0.710	0.711	0.800	0.740
	(0.454)	(0.454)	(0.400)	(0.439)
Household size	4.034	3.965	4.219	4.072
	(1.759)	(1.696)	(1.639)	(1.703)
Employed	0.437	0.442	0.490	0.456
	(0.496)	(0.497)	(0.500)	(0.498)
Owned land (acres)	1.062	0.754	0.788	0.872
	(1.908)	(0.866)	(1.337)	(1.452)
# plots owned	1.241	1.267	1.274	1.260
	(0.519)	(0.618)	(0.580)	(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	3.248	3.316
	(3.000)	(3.370)	(3.132)	(3.168)

Standard deviations in parentheses.

Table 2: Efficiency

	(1) Efficiency	(2) Efficiency	(3) Efficiency	(4) Efficiency	(5) Efficiency	(6) Efficiency
CDA Swap Auction	-0.006	-0.024	0.034	0.019	0.043	0.027
	(0.037)	(0.050)	(0.035)	(0.051)	(0.034)	(0.050)
CDA Package Auction	0.052	0.068	0.063	0.059	0.080	0.076
	(0.033)	(0.045)	(0.033)	(0.047)	(0.029)	(0.043)
Low Cash Treatment	0.002	0.001	0.002	-0.011	0.002	-0.010
	(0.022)	(0.046)	(0.024)	(0.053)	(0.024)	(0.053)
CDA Swap × low cash		0.035		0.031		0.031
		(0.056)		(0.062)		(0.062)
CDA Package × low cash		-0.032		0.008		0.008
		(0.058)		(0.063)		(0.063)
Block fixed effects	X	X	X	X	X	X
Within-session trends	X	X	X	X	X	X
Gender & Lab controls	X	X	X	X	X	X
Drop Block 1			X	X	X	X
Linear time trend					X	X
N	366	366	318	318	318	318
R-squared	0.184	0.186	0.105	0.106	0.111	0.112
Control group mean	0.678	0.678	0.702	0.702	0.702	0.702

Standard errors clustered at session level in parentheses. “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).

Table 3: Defragmentation

	(1) Defrag.	(2) Defrag.	(3) Defrag.	(4) Defrag.	(5) Defrag.	(6) Defrag.
CDA Swap Auction	0.000	-0.036	0.010	-0.036	0.014	-0.032
	(0.025)	(0.035)	(0.024)	(0.038)	(0.025)	(0.039)
CDA Package Auction	0.015	0.021	0.028	0.014	0.035	0.021
	(0.024)	(0.032)	(0.026)	(0.035)	(0.024)	(0.035)
Low Cash Treatment	-0.013	-0.033	0.001	-0.038	0.001	-0.038
	(0.021)	(0.041)	(0.022)	(0.047)	(0.022)	(0.047)
CDA Swap $\times$ low cash		0.073		0.091		0.091
		(0.049)		(0.055)		(0.055)
CDA Package $\times$ low cash		-0.012		0.028		0.028
		(0.054)		(0.055)		(0.055)
Block fixed effects	X	X	X	X	X	X
Within-session trends	X	X	X	X	X	X
Gender & Lab controls	X	X	X	X	X	X
Drop Block 1			X	X	X	X
Linear time trend					X	X
N	366	366	318	318	318	318
R-squared	0.137	0.144	0.060	0.068	0.062	0.070
Control group mean	0.840	0.840	0.862	0.862	0.862	0.862

Standard errors clustered at session level in parentheses. “Defrag.” measures the fraction of the potential gains from defragmentation achieved. 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: Improvement in sorting

	(1) Sorting	(2) Sorting	(3) Sorting	(4) Sorting	(5) Sorting	(6) Sorting
CDA Swap Auction	-0.069	-0.051	0.012	0.006	0.039	0.034
	(0.072)	(0.083)	(0.068)	(0.087)	(0.063)	(0.083)
CDA Package Auction	0.070	0.066	0.103	0.045	0.156	0.099
	(0.073)	(0.098)	(0.072)	(0.104)	(0.061)	(0.089)
Low Cash Treatment	-0.008	0.001	-0.005	-0.048	-0.005	-0.046
	(0.051)	(0.089)	(0.055)	(0.097)	(0.055)	(0.097)
CDA Swap $\times$ low cash		-0.035		0.014		0.012
		(0.116)		(0.128)		(0.128)
CDA Package $\times$ low cash		0.007		0.117		0.115
		(0.136)		(0.143)		(0.143)
Block fixed effects	X	X	X	X	X	X
Within-session trends	X	X	X	X	X	X
Gender & Lab controls	X	X	X	X	X	X
Drop Block 1			X	X	X	X
Linear time trend					X	X
N	274	274	238	238	238	238
R-squared	0.216	0.216	0.122	0.125	0.142	0.145
Control group mean	0.308	0.308	0.353	0.353	0.353	0.353

Standard errors clustered at session level in parentheses. "Δ Misalloc." measures the fraction of potential gains from sorting realized. 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: measure is not defined for maps 1 and 3.

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		1.003	
	(0.005)		(0.005)		(0.005)		(0.005)	
CDA Swap Auction		22.983		-12.192		-1133.683		-1011.872
		(880.578)		(763.216)		(673.148)		(617.819)
CDA Package Auction		-1092.711		-1100.053		-1139.816		-988.367
		(655.485)		(664.334)		(650.374)		(608.127)
Low Cash Treatment		-495.043		-496.260		-312.128		-307.325
		(470.473)		(470.529)		(492.667)		(490.478)
Constant	-1.873	5346.137						
	(3.164)	(1143.069)						
Block fixed effects			X	X	X	X	X	X
Within-session trends	X	X	X	X	X	X	X	X
Gender & Lab controls	X	X	X	X	X	X	X	X
Drop Block 1					X	X	X	X
Linear time trend							X	X
N	2196	2196	2196	2196	1908	1908	1908	1908
R-squared	0.914	0.004	0.989	0.126	0.990	0.126	0.990	0.127
Mean dep. variable	542.311	3761.695	542.311	3761.568	546.947	3423.564	546.947	3423.558

Standard errors clustered at session level in parentheses. 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).