Village fairness norms and land rental markets

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Abstract

Participation by smallholder farmers in land rental markets remains low in most of Sub-Saharan Africa. This paper describes the scale and role of fairness norms in such markets in rural Malawi. We document the presence of inequity averse preferences, which map into fairness norms, as measured by a modified dictator game. We establish a relationship between fairness norms and land rental markets across 250 villages in Central Malawi. Stronger fairness norms correlate with a tighter range in rental rates for agricultural plots, thereby increasing the minimum accepted rate and reducing the maximum accepted rate. We show that land market adjustments to weather shocks are limited, another effect of the fairness norms we document.

Key words: fairness norms, land rental, land markets, Sub-Saharan Africa, Malawi
JEL: D63, D71, O12, Q13, Q15

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1 Introduction

Though arable land is a key component of production in low-income countries, farm household rights to the property they cultivate are often poorly defined. Farming in Sub-Saharan Africa often involves small fields cultivated by households where land tenure systems are customary and communal, meaning that the land is owned by a kin-based or political group and that individuals obtain the right to cultivate through membership in that group (Udry, 2011). Customary and communal land tenure systems result in flexible and negotiable local systems of land tenure (Boserup, 1985; Takane, 2008). These systems abide by local norms and values that competitive market systems do not always allow. Kinship land-sharing, for example, can promote cooperation (Sadoulet, De Janvry, and Fukui, 1997), while land assignment made exclusively according to community leader preferences can restrict reallocation (Giles and Mu, 2018).

Customary land tenure systems are often grounded in notions related to fairness and equity (Barrett, 1996; Holden and Otsuka, 2014; Muyanga and Jayne, 2019). For example, restrictions may serve to prevent distress sales in a context of weak or missing credit and insurance markets (Deininger and Feder, 2001; Ricker-Gilbert et al., 2019).[1] Cultural restrictions can also help prevent speculative land accumulation. For example, Zhao (2020)'s analysis of China's 1980s and 1990s household responsibility system of land tenure in the 1980's and 1990's shows that the labour-contingent manner of allocating land decreased within-village inequality across households.[2]

In this paper we study in detail one dimension of customary land tenure systems: how prevailing social norms, and in particular norms related to fairness, influence the functioning of land rental markets in rural Malawi.

Though land rental markets are relatively thin in Malawi, the potential benefits of an efficient land rental market are estimated to be high. Approximately 17 percent of rural households participate in land rental markets annually according to Malawi's Integrated

[1] A substantial literature examines the role of land tenure security in agricultural development, technology adoption, and migration (Besley (1995), Goldstein and Udry (2008), and Brasselle, Gaspart, and Platteau (2002)).

[2] Beck, Bjerge, and Fafchamps (2019) also notes the importance of kinship ties when reallocating land in Uganda.

Household Panel Survey (IHPS 2010, 2013, 2016).[3] Restuccia and Santaeulalia-Llopis (2017) estimate that Malawi's aggregate agricultural output could increase by a factor of 3.6 were landholdings reallocated to their most efficient use among existing farmers.[4]

There are reasons to expect that fairness norms play an important role in Malawi's land relations. Kishindo (2004) notes that while customary land was perceived by Malawi's pre-1994 Banda government as a "reservoir from which private and public land can be obtained", access to land was considered a right of all Malawians. The essential role of local chiefs (who were in charge of customary land) was to ensure "equitable distribution of the land among the current generation and its preservation for future generations" (Presidential Commission on Land Policy Reform, 1999). Experimental studies have also documented other-regarding preference (Mueller, 2011; Goldberg, 2017), evidence that Malawi offers a relevant setting to study the role of social norms on the functioning and development of rental land markets.

We use detailed qualitative, quantitative, and experimental data on inequity averse preferences and fairness norms, and land market participation collected in 2018 from 2,500 households and 4,652 agricultural fields, in 250 villages in rural Malawi. We complement these primary data with data from the IHPS, and administrative weather data to provide a discussion of external validity. This rich data environment allows us to describe four new results that demonstrate the relationship between land markets and social norms.

First, we use our survey data to characterize household participation in land rental markets, and to establish the correlates of rental rates. In our sample of 2,500 rural households, 15 percent participated in the market as a tenant and 5 percent participated as a landlord, consistent with national-level statistics for the region (Deininger, Savastano, and Xia, 2017). Our analysis of rental rates demonstrates that while soil quality, market access, and field size are associated with higher rental rates, they explain only 30 percent of the observed variation.[5] Fields with markedly different soil and plot characteristics

[3]These percentages likely underestimate activity in land rental markets as landlords often under report their land rental activities for the fear of losing their land cultivation rights (Ricker-Gilbert, Mason, and Chamberlin, 2016) and many rural households opt in and out of the market from one year to the next.

[4]See also Chen, Restuccia, and Santaeulàlia-Llopis (2017) for evidence on Ethiopia, a country where land is owned by the state.

[5]This is broadly consistent with what we know determines rural land rental rates in developing

often feature the same rental price within a given village. Moreover, while active carbon, a measure of overall soil fertility, is approximately normally distributed across villages, rental rates are not normally distributed, and appear capped with focal points. In certain villages, we note bunching at the lower end of the distribution of rental rates, suggesting the presence of a minimum rental rate, protecting landlords. In other villages, we note upper-end bunching, indicating the possible presence of a maximum rental rate, protecting tenants. As a reference, while on average, tenants and landlords appear about equally wealthy in our sample (as measured by total asset value, excluding land), the average wealth of tenants exceeds the wealth of landlords in 60 percent of the villages.[6]

Second, we document the presence of inequity averse preferences using survey responses, and village-level variation in corresponding fairness norms using experimental data in the form of a modified dictator game.[7] In the survey, we asked the household head a series of questions related to whether they would consider hypothetical scenarios in the land rental market "very unfair", "unfair", "fair" or "very fair". The scenarios cover personal relationships, responses to shocks, and changes in market demand and supply. For example, the question: "Last year the rental rate was 15,000 Kwacha. This year there are more tenants seeking to rent land. One landlord decides to charge an increased rate, 17,000 Kwacha," elicits preferences regarding raising rental rates in response to increased demand. We use these data to compile two indices, measuring protection for tenants and landlords, respectively, and note a considerable degree of between-village variation.

We map these preferences with the results of a modified dictator game.[8] In a standard

countries. Ricker-Gilbert, Mason, and Chamberlin (2016), using national-level data from Malawi confirm the importance of these factors (see also Wineman and Jayne (2018), for insights on field values in Sub-Saharan Africa).

[6]This is consistent with Ricker-Gilbert et al. (2019) who, using a sample of matched tenant-landlords in Malawi, note the presence of reverse tenancy, where the tenants' wealth exceeds the landlords' in terms of durable assets (see also Bellemare and Barrett (2003)).

[7]The notion of inequity averse, or more broadly, other-regarding preferences, has received substantial attention since the concept was described in the early 1990s (Rabin, 1993; Bolton, 1991; Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000). In Bénabou and Tirole (2006)'s model of pro-social behaviour, people gain utility from thinking of themselves as socially minded, and the appreciation of others as such. Economic experiments have confirmed the presence of this type of behaviour (Braaten, 2014; Jakiela, 2015). As noted, in Malawi, Mueller (2011) and Goldberg (2017) have documented other-regarding preferences.

[8]The distinction between preferences and norms is notable, with the latter often describing equilibrium outcomes of behaviour (see Burke and Young (2011) and Bowles (2013) For instance, Kandori (1992), in an application of the Folk Theorem, shows how social norms can arise in situations where agents

dictator game, a dictator divides a fixed budget between herself and another, typically anonymous, participant. The amount shared with the other participant is commonly used as a measure of other-regarding preferences, whether a form of altruism or inequity aversion. In our case, we were interested in the behavior of the group. Hence, we modified this standard set-up as follows. In each village, we divided all participants into two random groups, and asked each group to make a series of choices (through a confidential majority vote). Each choice consisted of two payoff bundles: Bundle A (500 MK; 500 MK) and Bundle B (500 MK; 1000MK). In the first bundle, both groups receive 500 MK per person; in the second bundle, one group receives 500 MK per person while another group receives 1000 MK per person. This set-up corresponds to Kritikos and Bolle (2001) in the sense that participants are asked to choose between sets of two bundles.[9] Where we differ is in the participants' ability to discuss the bundles prior to making a group choice, as the fact that it is not the individual choice, but the group's choice that is implemented. The latter reframes the game explicitly as a group choice, drawing attention to any prevailing group norms.

Thirty-eight percent of the groups surveyed opted for Bundle A (the equal income distribution) when their group would have received the higher amount had they chosen B; 62 percent opted for Bundle A when their group would have received the lower amount had they chosen B.[10] When we randomized which group receives the larger amount in case of Bundle B (with the result of this randomization unknown to the participants at the time of the decision), 43 percent of groups still opted for Bundle A. This method corresponds with the idea of fairness as perceived by the participants during pre-testing and qualitative interviews. It also coincides with the axiomatic, and Rawlsian, concept of anonymity (Dasgupta, Sen, and Starrett, 1973). Hence, we use this, together with the

are purely self-interested, as long as these agents interact repeatedly with another. In an empirical application, Bartos (2016) notes the presence of stable inequity averse preferences regarding sharing rules in Afghanistan, but a varying degree of fairness norms Bartos (2016) argues that the reason for this difference between preferences and norms is that rules are not actively enforced during periods of scarcity.

[9] We note the earlier work of Fehr and Schmidt (1999) and Bolton and Ockenfels (2000) which associates a disutility with deviations from the average payoff.

[10] The latter is consistent with a plethora of laboratory ultimatum games in which participants routinely reject unfair offers (see, among others, Güth, Schmittberger, and Schwarze (1982)). The former adds to the more limited laboratory evidence on the dislike to be ahead of others (Fershtman, Gneezy, and List, 2012).

percentage of participants who voted for the Bundle A, to construct a measure of the strength of the fairness norm. We note that this measure is correlated, in an expected fashion, with the survey measures of inequity aversion.

Third, we analyse the relationship between village rental rates, rental market activity, and fairness norms. We compute the rental rate range for each of the 250 villages to characterize the bunching phenomenon. We find that stronger fairness norms correlate with a reduction in the range of the rental rate. These results are robust to the inclusion of a range of village-level controls and various approaches to measuring the rental rate range. Breaking down the effect of rental rate range into the effect on the minimum and the maximum rental rate permits a better understanding of the role of norms. Strong fairness norms not only lower the maximum rental rate, but also, to a lesser extent, increase the minimum rental rates.

Finally, following Kaur (2019), who studies fairness norms in India's rural casual labor market, we exploit the geographic variation in the IHPS to document the response of the rental rate to rainfall shocks. Results suggest that the land rental rate responds differently to positive versus negative agricultural productivity shocks. If fairness norms are present, one would expect a subdued response to market shocks, as the norm is likely to enforce the socially accepted minima or maxima.[11]

We find suggestive evidence that when a given community experiences two consecutive years of poor rainfall, the rental rate drops; but when a community experiences two consecutive years of good rainfall, the rental rate appears not to adjust. This pattern indicates that the minimum rental rate, which protects landlords, can be shifted in these extreme circumstances of possible famine (as we know that more severe food crises are associated with back-to-back poor harvests, see Gráda (2009)). Results from an analysis in which we split the sample into strong and weak norm communities further confirm

[11]Kaur (2019) reports an upward adjustment to the nominal wages of casual labourers to a positive rainfall shock, but no downward adjustment. The asymmetric response is consistent with descriptive evidence that the ratcheting protects the landless labourer. While the effect on land markets might be more complex, as the rainfall realisation effectively precedes the payment of the rents, rainfall shocks affect agricultural productivity (Alfani et al., 2019; Asfaw et al., 2019; Dell, Jones, and Olken, 2014; Jayachandran, 2006; Mungai et al., 2016; McCarthy et al., 2021), which, in turn might create local wealth effects, pushing up rental rates.

that only weak norm communities see a decrease in rental rates following a year of poor rainfall.

We are unaware of previous attempts to quantitatively analyse the role of social norms in rural asset markets, and land in particular. Social norms have been found to impact the functioning of a range of economic institutions including labour markets in developing countries (Goerges and Nosenzo, 2020; Kaur, 2019). With respect to agricultural production, social structures and relations can enhance agricultural productivity by providing insurance, credit and information (Jakiela and Ozier, 2016; Platteau, 2000). However, because data limitations have impeded attempts to quantify the influence of social norms in rural asset markets, our paper contributes by demonstrating an important role played by fairness norms in land markets in the Malawian context.

The paper proceeds as follows: Section 2 provides some background information on Malawi. Section 3 provides an overview of the data collected. Section 4 presents the descriptive analysis and Section 5 presents the regression analysis of land market outcomes on fairness norms. In section 6, we introduce Malawi's IHPS and explore how the land rental market responds to rainfall shocks. Section 7 concludes.

2 Rural Malawi

Malawi is a landlocked country in Southern Africa with over 50 percent of the population living below the poverty line (FAO, 2015). More than 80 percent of the country's rural population derive their livelihoods directly from agriculture (Chinsinga, 2011; FAO, 2015). The country maintains three types of land tenure systems: private (freehold or leasehold), public, and customary (or traditional) (Ricker-Gilbert et al., 2019). Most farmland in rural Malawi is held under the traditional tenure system. Lunduka, Holden, and Øygard (2009) report that in the 1970s, about 80 percent of all arable land was held under the traditional tenure system, and by 1997, still less than 10 percent of all arable land held under the customary system had been converted to private land. In this customary system, a household gains access to farmland either through direct allocation by the village headmen, or through the inheritance of perpetual user rights.

Farm plots in rural Malawi are small (with average land holding size of 0.75 ha in Central Malawi) and demand for land is increasing due to population pressure (Chamberlin and Ricker-Gilbert, 2016; Deininger and Byerlee, 2011). While land sales have been used elsewhere as a means of facilitating land transfer, the lack of tenure security renders this practice unusual in rural Malawi (Peters and Kambewa, 2007; Peters, 2013). Land rental markets have stepped in as a means of transferring land between households (Tione and Holden, 2020; Holden and Otsuka, 2014; Holden, Otsuka, and Place, 2010). However, as noted earlier, participation in these rental markets remains limited to date (IHPS). The lack of tenure security has been offered as an important factor limiting households' participation in the rental market (Holden, Kaarhus, and Lunduka, 2006; Holden, Deininger, and Ghebru, 2011).

As a means of redistributing land from large estates to smallholders as well as improving tenure security, Malawi adopted the National Land Policy in 2002 (FAO, 2015). This policy sought to protect smallholders' land rights and safeguard poor land users' interests with the goal of facilitating the development of land rental markets. The policy has been amended since its initial adoption, including the passing of the Land Bill and the Customary Land Bill in 2013 (FAO, 2015). The most recent Customary Land Act, which took effect in 2018, fosters registration of customary land as private land, in hopes of boosting productivity through increased investment, as well as increased participation in land rental markets.

3 Sample and data collected

Data was collected as a part of an impact evaluation conducted with an NGO, the Clinton Development Initiative (CDI) designed to understand how farmers learn from extension services and adapt to new output markets. This impact evaluation is not the object of study in this paper, however, and the data collected for this paper were collected mostly at endline with the specific purpose of studying the land markets in the region.

Together with CDI, we selected two districts in Central Malawi where the NGO had not yet expanded their operations: Kasungu district and Dowa district. Within these, we selected two EPAs (Extension Planning Areas, a sub-district administrative unit): Chibvala in Dowa district and Mtumthama in Kasungu district. We sampled 250 villages, and 10 households living in each village, yielding 2500 households in the sample.

We collected two rounds of panel data: one round in 2014 and a second in 2018. In our analysis we focus on the 2018 round, even though we will present some descriptive statistics from 2014. We collected quantitative, qualitative, and agronomic data at three levels: village, household, and field, and conducted a modified dictator game within each village.

3.1 Sample

In 2014, we obtained a list of all villages in the two selected EPAs from the 2014 village census listing of the District Agricultural Offices. This list included a total of 360 villages. We randomly selected 250 from the 303 villages that consisted of at least 50 households, stratified by EPA.[12]

We generated a census of all households within these 250 villages. We used this census to draw a random sample of 10 households for each village. In the treatment villages of the aforementioned impact evaluation, we stratified the household sample and sampled five participant households and five non-participant households (as participation into the program was voluntary).

Given that we are interested in the land market in this paper, it is possible that using a random sample of households, rather than household census, or random sample of fields, could have resulted in very few landlords included in the sample. In 2018, we find that five percent of households rented out land, while 15 percent rented-in land (see Table 1). In addition, even if included in the sample, landlords might under-report their participation in the land rental market. Deininger, Savastano, and Xia (2017) using the Malawi's Living Standard Measurement Survey note that rented out land represents only

[12] As CDI works through farmer clubs and the functioning of these clubs requires a minimum village size, we excluded the villages with less than 50 households.

six percent of the rented-in land. One of the reasons might be that landlords rent to multiple tenants. Ricker-Gilbert et al. (2019) using data collected among 600 matched landlord-tenant pairs within the same region note that 20 percent of landlords had more than one tenant.

In our case, we expect that this method of sampling plays a limited role, and does not to constitute a source of bias. Unlike Ricker-Gilbert et al. (2019) we do not attempt to estimate the welfare or efficiency consequence of rental market participation on households (see also Chari et al. (2020)). Our analysis uses field level data on rental rates, mapped up with statistically representative village level fairness norms (as the measure of the norms are based on a random sample of the population within each village). As 62 percent of land transactions happen with individuals or entities from inside the village, the within-village norms are the relevant norms. While the field-level data can be expected to display a certain degree of clustering at the household level, as the households were randomly sampled, we do not have any a-priory reason to expect certain types of field to be over or under-sampled.

3.2 Data collected

We administered a household survey among the head of the household of each of the 2500 households, eliciting information on household assets, composition, landholding and land relations, as well as equity preferences. For a randomly selected subset of this household sample, we collected and analysed soil data. Throughout the 2014-2018 period, we collected qualitative data through focus group discussions and individual structured interviews. We detail these data sources below.

In 2014, we also administered a village questionnaire in each of the 250 villages with a knowledgeable individual, often the village head. The village questionnaire aimed to collect information on the village-level factors that are known to play a role in land markets. Hence, we collected information on village market access (distance to farm input markets, paved roads, etc.) and recorded the location of the village center using GPS. In addition, inspired by the literature on ethic fractionalization and institutional performance (see, for instance, Easterly, Ritzen, and Woolcock (2006) and Miguel and Gugerty (2005)), we followed the Malawi's IHPS, and added questions on population, ethnicity and civil and religious organizations. In 2018, we added questions on migration, trust levels, willingness to contribute towards public goods and willingness to help one another.

3.2.1 Quantitative data

In both years, we collected data on household assets, composition and group membership. A key component of our questionnaire covered landholding, which included ownership, decision-making, land rents and soil quality. In 2018, we introduced a series of questions on inequity aversion.

Land rents

We started off with a series of questions on field ownership and status which guide the remaining questions. We asked information on all fields owned and/or cultivated.

For all owned fields, we elicited the estimated sale value of the field (in Malawian Kwacha, MK) and, importantly, the estimated yearly rental rate, also in MK. This question was phrased as follows: "What would be the yearly rental value of this field?" Eliciting both the realized and the hypothetical rental rates by field is also done in the IHPS (Julien, Bravo-Ureta, and Rada, 2019; Ragasa and Mazunda, 2018; Sibande, Bailey, and Davidova, 2017). During pre-testing we noted that this hypothetical phrasing was well understood by respondents, as all were familiar with the concept of land rentals. In effect, all the villages exhibit some degree of rental activity (see Table 2).

For fields that were cultivated, but not owned, and hence rented-in, we inquired about the actual rental rate as follows: "What is the rental rate?" Similarly, for fields which were owned and rented out, we asked for the actual rental rate. The respondent had the opportunity to indicate whether this rental rate was as a share of the output, or a nominal fixed value, and, if the latter, when the payment was made.[13] In the 2018 round,

[13] It should be noted that in 2014, we did not distinguish between owned fields which were rented out and owned fields which were not rented out. As such, we have no estimates of the rental rates of rented out fields in 2014.

we also asked the respondent to indicate who the rental rate business partner was. As noted earlier, 62 percent of rental contracts were within-village (see Table 1).

In the 2018 round, we also asked the respondent to indicate the reference period (yearly versus seasonal).[14] Unlike in other parts of the world, where sharecropping is dominant, it is notable that the large majority of land rental contracts are single-year, fixed rent contracts, with payments made at the start of the main rainy season (see Table 1). In Malawi, the main rainy season starts in November and ends in April. Irrigation infrastructure which can support all year-round farming is not well developed, hence most agricultural production activities occur in the main rainy season.

This fixed rent structure allows us to compare and validate our hypothetical rents question, as both cover the same time period (one year), and use the same unit of reference (Malawian Kwacha). Figure A.2 of Appendix A, overlays the kernel density estimates of the hypothetical and actual per acre rental rates for the 2018 survey round.[15] The graph shows a strong overlap between the hypothetical and actual rental rate distributions (although a Kolmogorov-Smirnov test rejects the equality between the two distributions, with a p-value of 0.000). Table 1 notes an actual rental rate of 20,000 MK per acre, compared to a hypothetical rate of 23,000 MK per acre; difference is relatively small but statistically significant. In the analysis we use the hypothetical rental rate which allows us to avoid small sample issues associated with using the actual rental rate (as few households rent land in or out in any given year).

We followed up information with information on perceived soil texture, soil fertility, soil depth, field location and cultivable and cultivated acreage. In 2018, we added questions on field shape, and ownership (in particular, who in the household inherited the field). Following best practices, we randomly selected a subset of households to measure the field acreage via GPS. This avoids the commonly reported measurement errors introduced by

[14] In the survey, we distinguished between rented-in land as land borrowed for use for one or a few season in return for money or output in-kind, and leased land, which is land that has title and the user has the right to occupy and use the land for a specified term. In our analysis, we make no such distinction.

[15] We drop the 2014 round from this analysis as in this round we joined the owned fields which were rented out with those which were not rented out, which might provide an inaccurate estimate of the hypothetical rental rate in this round.

farmers' estimates (see, e.g. Desiere and Jolliffe (2018)).[16] For this same set of households, we collected and analyzed soil samples.[17] We return to this agronomic component of the data collection below. The average farmer reported field size is 1.95 acres while the GPS recorded field size is 1.45 acres, suggesting that farmers on average slightly over-report their field size. In the analysis, to take advantage of the full sample, we use the farmer reported field sizes in the calculation of per acre rental rates.

Inequity aversion

Inspired by the work of Kaur (2019), we directly elicited respondents' inequity preferences. We did so by asking households a series of questions regarding whether they consider hypothetical scenarios in the land rental market "very unfair", "unfair", "fair" or "very fair" (allowing for a "no opinion" option). The scenarios covered relationships, responses to shocks, and changes in market demand and supply of land. For example, the question: "Last year the rental rate was 15,000 Kwacha. This year there are more tenants seeking to rent land. One landlord decides to charge an increased rate, 17,000 Kwacha," inquiries about protection for tenants in the form of maximum rental rates. The question: "A landowner usually rents out an acre of land for 15,000 Kwacha. His son becomes sick and the medical bills are very expensive. He increases the rent to 17,000 Kwacha," asks about protection for landlords. And the question: "Last year the land rental rate was 15,000 Kwacha per acre. This year, there is a new buyer in the market for soy and tobacco, who is offering prices up to 15% higher compared to last year. Landlords increase this year's rent also with about 15%, from 15,000 Kwacha to 17,000 Kwacha," inquires as to how the rental rate responds to market shocks. The full list of questions is included in Appendix Table A.1. These questions were carefully pretested among non-sample respondents to ensure that the scenarios were relevant to their experiences and well understood.

At the start of this module, we asked the respondent whether the household partici-

[16] We compare the GPS measured field acreage with farmer reported field acreage to check if there is any systematic difference between the two. While we take advantage of the full sample by using the farmer report field acreage in our analysis, we use the GPS measured field acreage as a robustness check.

[17] We use the observed soil active carbon (i.e. a measure of soil quality) from the soil analysis to compare the quality of rented and owned fields.

pated in the land rental market either as tenant, landowner or both in the past 10 years. We use this information to categorise each household by their longer-term land rental participation status.

We noted that some of the questions were intended to capture preferences as they relate to the protection of tenants, while others relate more to the protection of landlords. Using each type of question, we compile an index. We code "very unfair" as 2, "unfair" as 1, no "opinion" as 0, "fair" as -1 and "very fair" as -2, and subsequently add the responses of the various questions. As Table 1 notes, the average score for the questions that relate to the protection of tenants is 3.49, while the average score for the questions that relate to the protection of landlords is 0.44. While one should exert caution in comparing these two averages (as the set of questions are quite different), it is notable that within each category, the correlation coefficients can be high, ranging from 0.12 to 0.44. In Appendix Table A.2, we report the detailed results of this survey. There are three take-aways.

First, all respondents are concerned with the welfare of tenants. Respondents value the relationships between tenant and landlords and report that these relationships are relevant to land rent changes: 78 percent of notes it is (very) unfair to increase the rent to one's regular tenant (scenario 1A) and 90 percent notes it is (very) unfair to increase the rent of a tenant in need even though land is scarce (scenario 9B). As a result, perhaps, many respondents (65 percent) appear to be "against" the market clearing mechanism, i.e., an increase in rent when land is scarce (scenario 8). Even more, 73 percent, are against a BDM style elicitation of the willingness-to-pay of tenants (scenario 6).

Second, while respondents express concern for the welfare of landlords, there appears to be an asymmetry in this concern. In scenario 4, almost 60 percent of respondents were against raising the rents accordingly. When the scenario is reversed, and we imagine a decrease in the market price, only 30 percent notes a corresponding decrease in rental rates to be (very) unfair. This does not however mean that there is no concern for landlords: in scenario 3, 46 percent of respondents report it is (very) unfair to decrease the rental rate, even when a tenant is in need.

Third, these equity preferences do not appear to depend on the status of the respondent's household, as either a tenant household or a landlord household. This suggests that these views might be subjective and personal, but do constitute a social norm, albeit perhaps an internal one (in the sense that no obvious social pressure was applied when eliciting these preferences as interviews were conducted in private), shared by many villagers. The intra-cluster coefficient is however still low, 0.05 (tenant inequity index) and 0.10 (landlord inequity index).

3.2.2 Agronomic data

We collected soil samples from a total of 521 households' fields both in 2014 and 2018.[18] We used standard sampling practices and collected cropping and management history for each field. Appendix C describes sampling and lab testing methods.[19] Figure 1 presents the histogram of the distribution of observed land quality measured by active carbon in 2018. Looking at the variation within and between villages, we note an intra-cluster coefficient of 0.56. While significant, it also indicates that there is still substantial variation in soil quality within each village. This is consistent with other recent studies (Berazneva et al., 2018; Tittonell et al., 2005) As soil quality affects the agronomic potential, this within-village dispersion in soil quality can potentially play an important role in pushing the dispersion of soil rental rates within the village (Wineman and Jayne, 2018; Ricker-Gilbert, Mason, and Chamberlin, 2016).

[18] The villages were selected as follows as part of the impact evaluation: 10 purposefully selected treatment villages as they received the highest level of treatment, 20 randomly selected treatment villages, 9 randomly selected control villages and 10 villages purposefully, for their relatively higher share of female-headed households. We collected a soil sample from all ten sample households in these villages. As many farmers cultivate more than one field, we asked farmers to identify the field they would be most likely to try new technologies on. Farmers are more likely to select fields they own, fields of mixed soil texture, and fields with a higher incidence of soil erosion and nutrient depletion.

[19] The key indicators of land fertility in the study area are soil pH and organic matter content (Snapp, 1998). We analyzed sample pH, nitrate nitrogen (NO_3^-), inorganic phosphorus (P), sulfur (S), exchangeable potassium (K) and electrical conductivity (EC), and active carbon (C). Active carbon is relatively sensitive to near-term management (Marenya and Barrett, 2009), and more closely related to soil productivity and biologically mediated soil properties, such as respiration, microbial biomass and aggregation (Weil et al., 2003).

3.3 Qualitative data

We conducted focus group discussions in January 2016 and in January 2018 focusing on land inheritance, land rental rates and their determinants and perceived soil fertility within villages and across fields. This first set of interviews initiated the present study, as we noted a surprisingly lack of variations in land rental rates, and respondents pointed at the role of non-economic factors as determinants of these rates. We used a second set of interviews to elucidate the role of fairness norms, and tried out a whole host of games to capture these norms. Finally, in August 2018, we returned to six non-sample village to pre-test the inequity aversion survey instrument and the modified dictator game.

3.4 Modified dictator game

We played a modified dictator game in all 250 villages in 2018. We invited 22 individuals from 22 unique households to participate in the game in each village. This number was decided on purposefully, as to provide a reasonable representation of the village (the average village has 75 households, see Table 2), and to avoid any ties in the subsequent votes during the game.[20] In each village, we divided all respondents in two random groups, and asked each group to make a series of choices (through a confidential majority vote). We will refer to each choice as a round in the game.

In each round, a choice had to be made between two payoff bundles: Bundle A (500 MK; 500 MK) and Bundle B (500 MK; 1000MK). In the first bundle, both groups receive 500 MK per individual; in the second bundle, one group receives 500 MK per individual while another group receives 1000 MK per individual. Note that Bundle B dominates Bundle A, and if post-game redistribution happens, this dominance could be strict. The group's choice was settled through a majority vote, i.e., it was the choice of the majority of the group members. To frame the choice further as a group's choice, we encouraged group members to communicate with each other prior to making their individual choices.

To visualize the process, each participant was given two colored cards (a BLUE card

[20] Our game participants included a member from all the 10 sample households in the village. The remaining 12 participants were randomly selected from among the list of interested participants in the village. If more than one member from the same household showed up, we randomly selected one.

and a RED card). The BLUE card represented a vote for Bundle A (500 MK, 500 MK) and RED represented a vote for Bundle B (500 MK, 1000 MK). We would like to note that within the Malawian context, these colors are devoid of any particular significance. To obtain a group's vote, we used a non-transparent cloth bag, in which participants could then drop the card of their preferred choice, either Bundle A or Bundle B. The non-transparency of the cloth bag, as well as the fact that we physically separated the participants when making their choice ensured confidentiality. This was important as we wanted to avoid well-documented direct social pressures (which we also observed during the qualitative rounds). While, we, the researchers, would count the votes of each group after each round, it is clear from this set-up that we also guaranteed anonymity, as we, the researchers record the total number of votes for each bundle, but do not know who voted for which bundle.

Table 3 introduces the three rounds. The three rounds differ based on which group receives the higher payoff in the case of Bundle B being selected. In round one, if a group opted for Bundle B, then members in that group received 1000 MK each while members in the other group received only 500MK per person. In the second round, if a group decided on Bundle B, then each member of the group received 500 MK while members in the other group received 1000 MK each. In round three, if a group decided on Bundle B the group to receive the higher amount (i.e. 1000MK each) was determined by a coin toss at the end of the game (so the result of this coin toss was unknown at the time of the decision). The full protocol of the game is provided in Appendix B.

At the end of the game, we implemented one of the group's decisions of one of these three rounds, randomly chosen (out of the six possible options). As the choices of the groups are not revealed as we progress through the game, we expect order effects to be of minimal concern. While some degree of learning about the game might be at play, and hence, order effects might still be a concern, we have no prior as to the degree to which this would be present in this setting as the literature has reported cases with significant order effects (as in Holt and Laury (2002) and Holt and Laury (2005) and cases without any evidence of order effects (as in Alpizar, Carlsson, and Naranjo (2011) and Harrison et al. (2005)).

While all three rounds measure some form of other-regarding preferences, the rounds differ in whom will receive preferential treatment. Consistent with past studies, we find that substantially fewer groups opt for equal distribution Bundle A (38 percent) in the first round, compared to the second round (where 63 percent opts for Bundle A). This suggest that inequality is especially disliked when one is behind others (see, among others, Güth, Schmittberger, and Schwarze (1982), Fershtman, Gneezy, and List (2012), and Charness and Rabin (2002). When we randomized which group receives the larger amount in case of Bundle B (and, recall, the result of this randomization is unknown at the time of the decision), 43 percent of groups opted for Bundle A.

In Figure 2 we present a histogram of the percentage of the participants in each village who voted for the equal distribution in Round 3. We note three focal points in this distribution at 0, 50 and 100 percent, with the largest number of villages at 50 percent. Zero percent means that no-one in the village voted for the equal distribution, while 100 percent indicates that all voted for the equal distribution. Together, these constitute about 40 percent of the villages. The largest mass is at 50 percent, seemingly suggesting disagreement within the village. However, one should keep in mind that each village had two groups, and if the two groups vote different from each other, each in a unanimous manner, this would also result in 50 percent. In effect, when consider the votes at the group level, rather than the village level, as in Figure 3, one can see that the mass at 50 percent disappears, and indeed most groups' vote was unanimous, meaning the group's participants appeared to have come to a consensus prior to the vote. The unanimous nature of the votes is not unexpected. Recall that the groups were encouraged to discuss their choices prior to each vote (although we maintained the participant's individual agency). [21]

As a comparison, Appendix Figure A.3 presents the results for Round 1 and 2. As

[21]In 56 percent of the villages, both groups voted for the same outcome in Round 3. Figure 4 reports on the distribution of the difference between percentage of members per group that opted for Bundle A and Bundle B in round 3. Note that the higher the percentage, the lesser the disagreement between groups. For example, difference 100 percent means there is no disagreement between the two groups in the village. Figure 3 shows that in most cases, the two groups in the village did not disagree in their voting.

one would expect, the mass of the distribution shifts towards the left in Round 1 (where one would receive 500 MK in in case of the unequal distribution) and towards the right in Round 2 (where one would receive 1000 MK in case of the unequal distribution).[22] Note that the elicitation technique of Round 3 corresponds to the axiomatic concept of anonymity within any measure of inequality, as indeed the identity of those who will receive the lower amount is unknown (Dasgupta, Sen, and Starrett, 1973). It is intuitively more aligned to what the respondents described as fairness, and, most importantly, significantly higher correlated with our various measures of equity aversion. In Table 4 We indicate the correlation between the percentage of participates who vote for the equal distribution in Round 3 and the inequity aversion survey questions. We note a reasonable strong correlation between the landlord index and the number of participants voting for the equal distribution. This correlation appears to be driven by the responses to question 7: "Last year land rental rate was 15,000 Kwacha. One landlord is in urgent need of money. In order to find a tenant, he decides to rent his land at 13,000 Kwacha. In the following weeks the landlord decides to rent his remaining land at 15,000 Kwacha."[23] In the analysis we use the number of participants that vote for the equal distribution in Round 3 as a measure of the strength of the fairness norm, but control for the range of the group level choices.

4 Descriptive analysis

We begin our analysis by describing patterns of the land rental market activity in the 250 villages. Household, field and contract summary statistics are reported in Table 1.

Panel 1 reports sample household characteristics (namely; sex, age, and years of education of household head, and household size). Column (1) reports the means and standard deviations of full sample, while Columns (2) and (3) reports on the means and standard deviations of tenant and landlord households, respectively. We note no

[22]The correlation between the participants in each village who voted for the equal distribution in Round 1 and Round 2 is 0.24 (with p-value of 0.0001)

[23]Reported in Appendix Table A.2 is a correlation matrix for all the inequity averse preferences scenarios in Appendix Table A.1

statistically significant differences between the landlord households and tenant households, apart from the age of the household head. On average, the head of landlord household is slightly older than tenant household. It is notable that the asset values of tenant and landlord households are comparable. Household asset value was calculated by summing the reported values of all household durable assets except land.

Panel 2 reports on household land ownership and rental market participation. In 2018, 15 percent participated as a tenant, while 5 percent participated as landlord (and 6 percent participated as both). Among households that rented-in land, the average payment made for a rented-in field was 20,255 MK per acre per year (27 USD) in 2018. The average payment received for a rented-out field was 17,829 MK per acre per year (24 USD) in 2018. In 2014, the average payment made was 13,238 (or 27 USD). The increase from 2014, in MK, 53 percent, is consistent with the inflation over this period. For the remainder of this section, we focus on the data collected in 2018, as these data map up with norms and preferences solicited in the same year (and also avoid some of the issues in classification between owned and rented out fields in the 2014 round). As noted before, actual rents paid are comparable to the hypothetical rents elicited through the question: "What would be the yearly rental value of this field?". In 2018, the hypothetical per acre and per year rental rate is 23,352 MK. Due to matters of sample size, we continue with our analysis with these hypothetical rental rates (as opposed to the actual rental rates).

These averages disguise substantial variation within and between villages.[24] In Figure 5, we plot the histogram of the (hypothetical) rental rates. The rental rate ranges from 1,000 MK per acre to 80,000 MK per acre, per year. Note also the long tail in Figure 5. In the analysis, we will work with the ln-transformed rental rate as presented in Figure 6. Doing so, renders this distribution almost normal. We now further explore the correlates of the rental rate. Table 5 shows the result of a regression of the logarithm of the hypothetical per acre rental rate on a constant (Columns 1 and 2), adding village location (Columns 3 and 4), adding field characteristics (Columns 5 and 6), and adding both village location and field characteristics (Columns 7 and 8). Columns 1, 3, 5 and 7

[24]Within village rental rates are often clustered at the lower end of the rental rate histogram. See Figure A.1 of Appendix A for the rental rate distributions of nine selected villages

present results without village-fixed effects; Columns 2, 4, 6 and 8 present results with village-fixed effects.

In equilibrium, absent any fairness norms, the village-level supply of land and village-level demand for land will determine the rental rate. Unlike sale prices, rental rates capture only the agricultural value of land, i.e., the annual returns of land (in terms of marketed and consumed agricultural production). This, in turn, depend on the market conditions and the characteristics of the field, such as, soil quality, plot acreage, location, and village-level characteristics such as market access and climatic conditions.[25] This is confirmed by looking at the regression correlates in Columns (3) and (5). Smaller, good quality fields with limited erosion located close to the homestead fetch a higher rent.[26] These field characteristics explain 14.7 percent of the variation. Fields in villages further away from markets and roads fetch lower rents. These location characteristics explain 6 percent of the variation. Together, in Column (7), they explain 17 percent of the variation.

A substantial amount of the remaining variation is at the village level. To illustrate this point, we add village-fixed effects. We note a jump in the R-square to 0.3 in Column (8). We postulate that the remaining village variation might relate to social norms. These social norms, in their turn, can be expected to be related to the socio-demographic conditions of the village. Most villages are ethnically homogeneous. Table 2 reports that 90 percent consists of individuals with the same ethnic background and the remaining 10 percent consist of individuals from two or more ethnic groups. Migration however is on the increase. Seventy-two percent of the villages reported an increase in the number of people leaving the village in recent years (that is, resettling elsewhere) and 65 percent reported that there has been an increase in the number of people moving into the village.

[25] Malawi has a tropical climate characterized by two main seasons, the wet season from November/December to March/April and a long dry season from April/May to October. Over 90% of farmers in the region rely on rainfed agriculture. Malawi has experienced recent changes in the onset of planting rains, poor rainfall distribution, droughts, and increased intensity and frequency of dry spells (Government of Malawi, 2006), with negative implications for agricultural productivity. Soils are generally low in organic matter (Snapp, 1998) and characterized by high variability in soil chemical properties (e.g. active carbon, nitrogen, inorganic phosphorus, potassium) and in soil texture between farms, with potential implications for crop choice and land rental rates.

[26] This is consistent with findings in Tittonell et al. (2005) that plots close to homesteads are more fertile than those that are further away in part because they benefit from the deposit of cooking ashes or of crop residues for crops that are processed at home.

So, while in and out migration might be substantial, overall net-migration is low, and only seven percent of the villages reported experiencing population reduction in recent years. In the analysis, we use this demographic information, and in particular, information on ethnic composition as a proxy for social norms within the village inspired by Easterly, Ritzen, and Woolcock (2006) and Nielsen (1985).

5 Fairness norms and the land rental market

To examine the relationship between rental rate and fairness preferences, we link the village-level rental rate measures with the village's strength of fairness norm through a regression, controlling for village confounders:

$$lnRentRange_v = \alpha_0 + \beta(Fairness)_v + \delta lnRentMedian_v + \boldsymbol{X}'_v\Pi + \epsilon_v \qquad (1)$$

where $lnRentRange_v$ is the natural log of per acre rental rate range for village v and $Fairness$ measures the strength of fairness norm in village v. The parameter, β is the estimate of interest and ϵ_v is the error term. We measure $Fairness$ as the percentage of participants in village, v, who chose the equal income distribution in round 3 of the modified dictator game. We include a control for a possible non-linearity around 50% by including two indicator variables: a dummy variable which equals one if exactly one group voted for the equal distribution, and a dummy variable which equals one if both groups voted for unequal income distribution. In addition, we include the percentage of participants who chose the equal income distribution in rounds 1 and 2.

Vector $\boldsymbol{X}$ includes variables measuring market access, population pressures, and migration. The selection of these variables was guided by literature on households' participation in the land rental market in Malawi (Chamberlin and Ricker-Gilbert, 2016; Abay, Chamberlin, and Berhane, 2021). Finally, we also include $lnRentMedian_v$ is the natural log of the median rental rate in village, v as to capture any further unobserved village-level characteristics which might affect the overall level of rents observed.

5.1 Main Results

Table 6 reports results from the estimations. Results reported in Column (1) do not include village controls; Column (2) includes village controls. Results are comparable across columns; we focus our discussion on the results reported in Column (2).

The findings in Column (2) indicate that a one percent increase in the strength of fairness norm is associated with a reduction in a village's rental rate range by 0.82 percent. Extrapolating this number, and interpreting it in a causal manner: if, for example, 40 percent of the households have strong inequity averse preferences, then the village's rental rate would be 32.8 (i.e. 40*0.82) percent lower than what it would have been in the absence of these fairness norm.

Whether the norm is associated with a relative increase in the minimum rental rate or a relative reduction in the maximum has implications: are norms serving to protect landlords or tenants, or both? In Table 7, we document the relationship between the strength of fairness norm and the village's minimum and maximum rental rates. While we find some evidence of both effects being present, the results indicate that fairness norms mostly act as a means of protecting tenants: the stronger the fairness norm, the lower the village's maximum rental rate. We find that a one percent increase in the strength of fairness norm is associated with a reduction in the village's maximum rental rate by 0.34 percent. This again suggests that if 40 percent of the households have strong inequity averse preferences, then the village's maximum rental rate decreases by 13.6 (i.e. 40*0.34) percent. The effect sizes on the minimum rental rate are similar, but no longer statistically significant, when including village controls. Results in Column (1) suggest that a one percent increase in the strength of the fairness norm is associated with an increase in the village's minimum rental rate by 0.37 percent.[27]

[27] We also report the results using an alternative outcome measures: the rental rate variance and absolute skewness in Appendix Table A.3. Consistent with the results reported in Table 6, we note that fairness norms are associated with a lower village rental rate variance: a one percent increase in the strength of the fairness norm is associated with a reduction in the rental rate variance by 1.28 percent. Although not statistically significant, we note that fairness norms positively correlate with rental rate absolute skewness, again suggesting that the stronger the norm, the stronger the degree of rental rate bunching. Figure A.4 presents the distribution of across-village rental rate skewness parameters. To strengthen the argument, we use the distribution of skewness parameters to divide communities into three groups: (1) community with a negative skewness parameter (i.e. negative bunching /"high norm"), (2)

While our descriptive statistics on inequity preferences noted some concern for poorer landlords, results indicate that overall the norms, as measured by the dictator game, may not adequately be protecting poor landlords by failing to pull the minimum rent up. In our context, landlords are not, on average, poorer than tenants (see Table 1). This is unlike other studies set in the area, see, among others, Ricker-Gilbert et al. (2019).

5.2 Ethnic diversity as a proxy for fairness norms

Earlier studies document the role of ethnicity in institutional development. Easterly, Ritzen, and Woolcock (2006) argue that social cohesion, strongly related in the African context to ethnic diversity, determines institutional quality and economic growth. Miguel and Gugerty (2005) demonstrate that ethnic diversity impedes community development in Kenya. In Malawi, ethnic diversity may impede cooperation, and proxy for local social norms (Dionne, 2015). We examine in Table 8 the relationship between the village-level rental rate statistics (range, minimum, and maximum) and the share of the village's population that belongs to the Chewa ethnic group, the dominant ethnic group in Malawi's Central region.

Results in Table 8 suggest that an increase in the share of individuals from the Chewa ethnic group in the village is negatively correlated with our measure of rental rate bunching (i.e. rental rate range), and the maximum rental rate. A one percent increase in the share of Chewa population is associated with a reduction in the rental rate range by 0.395 percent. A one percent increase in the share of Chewa population is associated

communities with zero/or close to zero rental rate skewness parameter (low bunching /"low norm"), and (3) communities with positive rental rate skewness (i.e. positive bunching /"high norm"). Communities with skewness parameters that are too far to the left or to the right of zero are classified as "high bunching / high norm" communities while those with skewness equal zero or close to zero are regarded as "low bunching/low norm" communities. We fit a multinomial logit model to examine the relationship between our measure for strength of fairness norms from the modified dictator game and the degrees of bunching (i.e."low norm"/"high norm") discussed above. We set communities with zero or close to zero skewness parameter (i.e. "low norm") as the base category. Given that not many communities have skewness parameters equal to zero, we define some neighborhood (i.e. epsilon) around zero to divided the sample into the three categories such that the higher the value of epsilon, the higher the norms in negative/positive bunching communities. The stronger the strength of fairness norms the stronger the degree of bunching. A plot of coefficients showing the relationship between the strength of fairness norms and the degree of bunching is reported in Appendix Figure A.5. As expected, the results indicate that estimated coefficients capturing the relationship between the strength of fairness norms and the degree of bunching increases with increasing values of epsilon.

with a reduction in the maximum rental rate by 0.244 percent. Although the signs are as expected, the estimate of interest loses its significance when we control for village characteristics including market access and population.

5.3 Fairness norms and land transacted

In Table 9, we present the relationship between rental market activity and the fairness norm. In Column (1) we consider the share of rented-in land (acreage, as ratio of total land owned) referring to the 2017-18 growing season. In Column (2) we analyze the number of households who participate in the land rental market in the 2017-18 growing season. In Columns (3) and (4) we study the number of households who have participated in the land rental market in the past ten years as tenant and as landlord. We note no statistically significant relationship in Columns (1) and (2), which assesses participation in land rental markets in only the 2017-18 growing season. When we consider households' long-term participation in the market in Columns (3) and (4), we note a positive, (but insignificant) correlation between the strength of the norm and tenant participation, and a negative correlation (and statistically significant at the 5 percent level) between the norm and landlord participation.

Fairness norms could also prevent markets from adjusting to other market considerations. Prevailing rental rates for example might not reflect the agronomic quality of fields. As rates are unable to adjust upwards, landlords of good quality fields might prefer to cultivate those fields themselves instead of renting them out. In Table 10 we present the results of a set of t-tests comparing the quality of rented-in fields with the quality of owned fields. The results reveal significant differences between rented-in and own-cultivated fields; overall, the own-cultivated fields are of superior quality. Our most reliable measure of field quality, soil carbon content, is about ten percent higher among own-cultivated fields compared to rented fields. We further elicited information on farmers subjective valuation of the quality of their soils. Thus farmers were specifically asked questions about whether their soil suffered degradation in the form of erosion, nutrient depletion, water-logging, salinity/acidity. Using these more subjective measures of soil quality, we note that owned fields are perceived to be of better quality than rented-in fields. Thus while about 50 percent of owned fields are reported to have good soil quality, just 43 percent of rented-in fields are reported to have good soil quality (however, own fields are more likely to suffer from soil degradation, in particular soil erosion).

In Table 11 we link these measures of soil fertility to the game-elicited fairness norms. In each column, we compute the number of rented-in fields with particular attributes as a share of the total number of rented-in fields. As the number of rented-in fields differs from one village to another, we weight the observations by the inverse of the total number of rented-in fields in each village. Though not quite statistically significant, we find a positive relationship between the share of rented-in fields which are eroded and the strength of the norm in Column (1) (though we cannot replicate these results using our more general soil degradation measure). Results in Column (2) suggest a negative relationship between the share of rented field with good fertility and the fairness norm. Similarly, in Column (3) we note a negative relationship between the strength of the norm and the share of rented fields with fine texture.

6 Land rental rate and transitory shocks

We seek to understand whether the relationships between fairness norms and land rental rates established in our primary data hold outside of our sample. We therefore extend our analysis using national-level survey data from Malawi. The challenge with secondary data is that we do not have any measures of fairness norms. However, we do have household-level panel data with information on land market participation and field-level inputs and outputs. Hence, we base our strategy on Kaur (2019). She studies the role of fairness norms in India's rural casual labor market. In this market, laborers work for a daily wage, harvesting and performing post-harvest operations. Using nationally representative wage data, she shows that wages increase in response to positive rainfall shocks, but do not respond to negative rainfall shocks. This ratcheting suggests the presence of a minimum wage, indicative of a social norm protecting these casual laborers, often the poorest in the village.

We similarly investigate the responsiveness of rental rates to transitory rainfall shocks in the years prior to our primary data collection. We use data from two sources: (1) household land rental activities from three rounds of Malawi's Integrated Household Panel Survey covering 2010 – 2016 (IHPS) and (2) rainfall data from Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS).

6.1 Secondary data description and summary statistics

The IHPS is the panel (2010, 2013, 2016) component of the Malawi's Integrated Household Survey is designed to monitor and evaluate the changing conditions of Malawian households. We describe the IHPS design and sample in the appendix. The IHPS tracked 1,989 households across 102 EAs (henceforth communities) from 2010 to 2016. IHPS collects information on agriculture, including field-level data on ownership and rental rate. The rental rates are captured by asking households to indicate, for each field, how much they would be willing to accept to rent it out for a period of 12 months.[28] The IHPS eliciation is comparable to our elicitation of the rental rate in our primary data collection. Given that our primary data is limited to only two districts (i.e. Kasungu and Dowa), we rely on rental rates in the IHPS to examine the relationship between rainfall shocks and rental rates over a larger geographic area. This allows us to exploit variation in rainfall across the country over three years.

We report IHPS summary statistics in Table 12. We note that rental rates are reported in constant 2010 Kwacha, using Malawi's Consumer Price Index (CPI). Farmer reported willingness to accept per acre rental rates increased between 2010 and 2016 even after adjusting for inflation. While farmers were willing to accept an annual rental rate of 4,969 MK in 2009 for an acre of farmland, in 2015 this rate had increased to 6,996 MK per acre. These per acre rental rates are consistent with the values observed in our primary data. According to our primary data, farmers were willing to accept 6,437 MK and 6,105 MK in 2014 and 2018, respectively. Households' land rental market participation remained

[28]The question in the IHPS questionnaire is "If you were to rent out this [PLOT] today for 12 months, for how much could rent it out?

relatively constant between 2010 and 2016. On average, 14 percent of households indicated they participated in the land market in all three rounds of the data. This number is in line with households' participation in the rental market reported in our primary data, where 15 percent of the households participated in the rental market in both 2014 and 2018. Household total cultivated crop acreage increased slightly between 2010 and 2016. Again, the average household cultivated acreage is consistent with the numbers in our sample.

The descriptive statistics show a slight reduction in the share of fields in the community under the production of food crops including maize and beans over time. Between the years 2010 and 2013, the average share of farmland in the IHPS sampled communities under cash crop production increased slightly from 0.21 to 0.23. However, the share of farmland under cash crop cultivation decreased slightly between 2013 and 2016.

Next, we turn to the rainfall data. The timing, distribution, and amount of the rainfall is critical to agricultural production. Malawi has three main agroecological zones: the high altitude, the mid altitude, and the low altitude agroecological zones. While these zones differ in their climate, soil characteristics, and topography, in each zone, the rainfall follows a unimodal pattern starting from October or November to March or April. Nearly all rural households are in Malawi are reliant on rainfed subsistence agriculture (Ricker-Gilbert, Jumbe, and Chamberlin, 2014). Erratic or inadequate rainfall affects yields. The unimodal pattern allows us to capture the adequacy of rainfall by simply looking at the total rainfall within this rainy season.

We follow Kaur (2019) and Jayachandran (2006) and use binary indicators to define positive and negative rainfall shocks. Our definition of rainfall shocks differ from Tione and Holden (2020) who define rainfall shocks as downside and upside deviations from average district-level rainfall. We define a positive shock in each season as rainfall above the 60^{th} percentile but below the 90^{th} percentile of the community's historical rainfall distribution. A negative shock in each season is defined as rainfall below the 20^{th} and above the 90^{th} percentiles of the community's historical rainfall distribution. Rainfall below the 20^{th} and above 90^{th} percentiles captures drought and flood periods, respectively.

We define a normal rainfall year as a year in which rainfall was greater than the 20^{th} percentile rainfall but less than the 60^{th} percentile of the community's historical rainfall distribution.

We compute these yearly totals from the daily rainfall series at Climate Hazards Group InfraRed Precipitation with Station (CHIRPS). CHIRPS is a 35+ year quasi-global rainfall data set, spanning 50°S-50°N (and all longitudes), from 1981 to the present day. CHIRPS combine station data with satellite imaginary to generate a high-resolution (0.05 degrees) gridded rainfall time series (see Funk et al. (2015) for a detailed exposition of CHIRPS). We extract the daily rainfall from 1981 to 2018 for each IHPS sampled community. We aggregate this daily rainfall and construct total rainfall estimates between the 1st of October and the 31st of May, representing the main growing season, to define rainfall shocks.

We report summary statistics for rainfall shocks in Table 12. Negative rainfall shocks have occurred with some frequency in recent years, consistent with the assessment of Kilic (2021). Recalling that the table reports lagged shocks with one and two year lags, respectively, one can see that in the 2008/09 agricultural season (IHPS 2010), about 80 percent of the communities either experienced drought or flood, while only three percent of the communities experienced a positive rainfall shock. Similarly, in the 2014/15 agricultural season (IHPS 2016) about 51 percent of the communities either experienced drought or flood, while only nine percent of the communities experienced a positive rainfall shock.

6.2 Estimation Strategy

In the absence of social norms, one would expect land rental rates to adjust to changes in local demand, driven primarily by changes in agricultural incomes. For smallholder farmers whose crop yields and farm income are largely determined by rainfall, changes in rainfall directly affect crop yield and income (see, among others, McCarthy et al. (2021), Stevens and Madani (2016), McCarthy et al. (2018), Azzarri and Signorelli (2020), Alfani et al. (2019), and Asfaw et al. (2019)). Over the last two decades, Malawi has been experiencing frequent droughts and also floods (Katengeza and Holden, 2021). McCarthy et al. (2021) show that crop yields and household incomes in Malawi are severely reduced by both droughts and floods, with average losses ranging between 32 and 48 percent.

Hence, rainfall-driven production increases can be expected to create local wealth effects that generate upward pressures on the rental rates. Conversely, negative rainfall shocks should put downward pressure on rental rates. Following Tione and Holden (2020) we expect this downward pressure to primarily come through landlords who increase the supply on the market through distress renting (this is also observed by Kusunose and Lybbert (2014) in Morocco).

We use the following regression specification to explore how rental rates adjust to rainfall shocks. We assume that rainfall shocks are identical and independently distributed.

$$lnr_{ict} = \theta + \phi_1 PosShock_{c(t-1)} + \phi_2 NegShock_{c(t-1)} + \mu_{round} + \rho_c + \epsilon_{ct} \tag{2}$$

where lnr_{ict} is the log of per acre rental rate of field i, located in community c, at time t, $PosShock_{(ct-1)}$ and $NegShock_{(ct-1)}$ are binary indicators for previous season's positive and negative rainfall shocks respectively. μ_{round} is a vector of dummies for the IHPS 2013 and IHPS 2016 survey rounds capturing time trends; ρ_c captures community fixed effects; and ϵ_{ct} is the error term.

In the absence of fairness norms, we expect $\phi_1 > 0$ and $\phi_2 < 0$. However, if such norms are at work, then rental rates may not respond as hypothesized and ϕ_1, ϕ_1 would equal 0. While we recognize that alternative explanations might also result in a similar non-response, we note that our results in this section should be viewed as merely indicative, consistent with the presence of social norms but not exclusively due to them.

Two aspects of this specification require particular attention. First, our definition of shocks. Following the previous exposition, we define a positive shock ($PosShock_{(ct-1)}$) as equal to one if the rainfall in community c in year $t-1$ is above the 60^{th} but below the 90^{th} percentiles of community's historical rainfall distribution. Conversely, a negative shock ($NegShock_{(ct-1)}$) is defined as equal one if the rainfall for community c in year $t-1$ is below the 20^{th} and above the 90^{th} percentiles of community c's historical rainfall distribution. The omitted rainfall category is normal rainfall with rainfall greater than the 20^{th} percentile but less than the 60^{th} percentile of the community's historical rainfall distribution. It is notable that we use rainfall of the previous season, and not the same season as in Kaur (2019). Kaur (2019) investigates effects in casual labor markets, which responds to rainfall shocks in the contemporaneous season, as laborers are employed mostly at harvest time. In contrast, land rents in Malawi are paid prior to the start of the season. Hence, it is mostly prior season rainfall shocks which determine the financial position of farmers. Tione and Holden (2020) show that in Malawi one-year and two-year lagged downside rainfall shocks appear to increase land market participation, an effect they attribute to distress renting. While expectations with respect to the next season might play a role as well, it is notable that both qualitative interviews and past research confirms that forming these expectations is not straightforward. When asked about their expectations of the next season, most farmers refer to what happened in the past 10-15 years, and by and large do a poor job predicting the next seasons' rain (Guido et al., 2020).

6.3 Main results

Table 13 presents the main results. We use the log of per acre rental rates as the dependent variable and note that this rental rate is scaled by farmer reported farmland size. Although we have data on GPS recorded farmland size, we use farmer reported farmland size to ensure consistency between the secondary and our primary data analysis. As a robustness check and as well as acknowledging the potential systematic differences between farmer reported farmland size and GPS recorded (Kilic et al., 2017), we replicate the regressions reported in Table 13, where we use the natural log of rental rate scaled by GPS recorded farmland size. Results of this estimation are reported in Appendix Table A.4 and are generally consistent.

Specification (1) includes only positive and negative rainfall shocks observed in the previous agricultural season as specified by equation (2). Specification (2) extends specification (1) by including positive and negative rainfall shocks observed in the previous two seasons and specification (3) adds rainfall shock interaction terms, allowing for the presence of non-linearities in response to sequences of realized shocks. Results reported in specification (1) indicate that neither negative nor positive rainfall shocks observed in the previous year has any significant effect on land rental rate. Specification (2) too yields no statistically significant relationship.

To allow for non-linearities in response to sequence of realized rainfall shocks, we focus on specification (3). The results reported in specification (3) indicate that, relative to a normal year, there is a significant reduction in rental rates when a community experiences two consecutive years of bad rains: two consecutive years of negative rainfall shocks reduce rental rates by about 7.7 (i.e. (0.039 + 0.111 - 0.225)*100) percent. We note that while the estimate for the non-linear term for two consecutive bad rainfall (i.e. 0.225) is significant at the 10% level, we fail to reject a joint test of significance for (0.039 + 0.111 - 0.225 = 0) at a p-value of 0.25.

Two consecutive seasons of bad rains are often considered a leading indicator of food crisis (Verdin et al., 2005; Funk et al., 2008; Battisti and Naylor, 2009; Kinda and Badolo, 2019). Such crises are associated with collapse of demand and increase in distress renting in a community. Indeed, previous empirical findings in the region note that households use land rental markets as a coping strategy in the form of distress land rentals when they experience negative rainfall shocks (Gebregziabher and Holden, 2011; Kusunose and Lybbert, 2014; Tione and Holden, 2020).

While two consecutive seasons of bad rains somewhat reduce rental rates, we find no evidence that two consecutive seasons of positive rains affect rent. This suggests that while tenants may be benefiting from rent reduction due to two consecutive years of bad rains, landlords do not share this benefit when the communities do well in periods of positive agricultural harvest. While positive rainfall shocks result in increased crop yields and farm incomes, such gains do not appear to translate into rate changes in the land rental market.

This asymmetric response in consistent with our results in the previous section. It is also consistent with the descriptive statistics of inequity averse questions, which suggested that the market rate responds differentially to positive versus negative shocks to agricultural productivity, and, indicated less protection for landlords. Recall the question: “Last year the land rental rate was 15,000 Kwacha per acre. This year, there is a new buyer in the market for soy and tobacco, who is offering prices up to 15% higher compared to last year. Landlords increase this year’s rent also with about 15%, from 15,000 Kwacha to 17,000 Kwacha.” We also inquired about the opposite scenario, where the rent would be decreased by 15%. In the case of the increased rent, 58 percent of respondents noted this to be “very unfair” or “unfair”; while in the case of the decreased rent, only 30 percent of respondents noted this to be “very unfair” or “unfair” (see Appendix Table A.1).

As a robustness check, we also compute the skewness of the rental rate distributions within villages and find that the strength of the fairness norm is positively correlated with rental rate absolute skewness. We can use this skewness parameter to split the sample into low and high norm communities. Figure 7 shows a distribution of community rental rate skewness parameters and the cutoff. Results of the split sample analysis are reported in Table 14. It is notable that in low norm communities, a negative rainfall shock in the previous season decreases rent by 12.5 percent while in high norm communities neither negative nor positive rainfall shocks in the previous season affect rent. These results suggest that the estimated effects may be driven by the communities where the social norm is relatively weak.

To meet food security needs as well as to ensure sustained household farm income, smallholder farmers are known to alter their crop choices in a response to rainfall shocks (Agamile, Dimova, and Golan, 2021; Bezabih and Di Falco, 2012). When times are good, farmers might take additional risks and increase their acreage under cash crops (although the opposite is reported by Agamile, Dimova, and Golan (2021) by women farmers in Uganda). To illustrate that the previous results are not due to an incorrect specification, or perhaps measurement of rainfall shock, we now consider the farmers’ responses in terms of their crop choices. We report the results of a random effects Tobit regression on the relationship between rainfall shocks and land allocation in Table 15.

Specification (1) uses the share of farmland under food crop production (in the community) as the dependent variable. Specification (2) uses the share of farmland under cash crop production (in the community) as dependent variable. These two specifications mirror each other: as the share of food crops goes up, the share of cash crops goes down (and vice versa).

The results reported in Table 15 indicate that, relative to a normal year, when a community experiences two consecutive years of bad rains: the share of land allocated to both food and cash crops does not change significantly.

While two consecutive seasons of bad rains do not influence land allocation, we find evidence that two consecutive seasons of positive rains does affect land allocation. The results suggest that, relative to a normal year, a community that experiences two consecutive years of good rains decreases the share of land under food crop production by about five (i.e.(0.00437 + 0.0617 - 0.120)*100) percent and increases the share of the community's land under cash crop production by about six (i.e. (0.00704 - 0.0431 0.100)*100) percent.

7 Conclusion

Cultural inheritance, including the social norms and practices influencing decision-making in communities across the world, plays an important role in shaping economic outcomes (Michalopoulos and Xue, 2021; Ananyev and Poyker, 2020; Jang and Lynham, 2015). In this paper we study how prevailing social norms, and in particular norms related to fairness, influence the functioning of land rental markets in rural Malawi.

We document price stickiness in land rental markets across Central Malawi using primary data we collected in the form of farmer surveys and a dictator game, the latter modified to elicit individual and group preferences for equal distribution of resources. These measures suggest strong norms oriented towards fair distributions over Pareto superior, but unequal, distributions. We show that these measures of fairness preferences are strongly and robustly associated with land rental prices. Linking these norms to land markets, we find that the observed range of the per-acre land rental prices shrinks as the experimental measure of salience of the fairness norm increases even after controlling for confounding factors including population pressure, market access, and in and out migration.

While we document the presence of fairness norms for both tenant and landlords, we note that the fairness norms for tenants appears to be quantitatively more important. We show that, more often than not, the land-rental price range is constrained by a price ceiling rather than a price floor.

We seek to understand whether these patterns hold outside of our sample, and extend our analysis using national-level survey data. We find evidence of land rental price stickiness in the larger sample; we show that rental rates neither increase nor decrease as a function of agricultural income shocks stemming from the prior season's rainfall. Rather, prices only decrease when a community experiences negative shocks across two successive years, although we do observe a response in the sub-sample of communities with relatively weaker norms. Again, this asymmetric response benefits tenants more than landlords.

The results of our study suggest several new areas of research.

First, our analysis is primarily descriptive, documenting the presence of fairness norms through survey and game data, and providing an indicative analysis of the scope of their role in Malawi's land rental markets. We have not investigated the origins or historical evolution of these norms, the subject of substantive contributions in evolutionary biology, game theory and social psychology (Young, 2015; Henrich, 2017; Henrich and Muthukrishna, 2021; Ananyev and Poyker, 2020). For example, Guerriero (2019) notes a relation between climate, terrain, and agricultural conditions and today's norms of cooperation in Europe. Is it possible that the fairness norms we document emerged because of some prior socio-environmental circumstances leading to differential distributions of wealth?

In our context, social customs regulated access to land in rural Malawi until the Customary Land Act of 2018. Inheritance rules in patrilineal and matrilineal societies dictated who inherits the land, and village chiefs acted as arbitrators (Takane, 2008) (although increased population pressures on land, increased male mortality due to HIV/AIDS, and increased rural to rural migration have pushed for some degree of flexibility, see (Takane, 2008). As such, further investigations on the origins of the fairness norms may start by a documenting existing practices of sharing and distribution (as in Jakiela (2015)), the villages' characteristics (as in Iacobelli and Singh (2020)) and movement/migration in and out of the villages (Fafchamps and Hill, 2019; Luke and Munshi, 2011).

Second, connections can clearly be made between the fairness norms we document and other economic processes in low income countries. The presence and implications of incomplete and imperfect markets has been a central feature of economists' understanding of behaviour, poverty, and inequality in low income countries (Stiglitz et al., 1988). Explanations of African farmers' lack of technology adoption (including opting out of market participation), have included market constraints, uninsured production risk, high transactions costs, heterogeneous returns, farmer learning, and intra-household dynamics (Singh, Squire, and Strauss, 1986; Duflo, Kremer, and Robinson, 2011; Karlan et al., 2014).[29]. If social norms are another form of constraints, how can we expect their role to change when some of these other constraints are lifted? For instance, when insurance markets expand, or the technologies introduced are 'progressive' in nature?

Malawi has recently initiated policies to supplant customary use with formal land ownership. Malawi's Customary Land Act[30] fosters registration of customary land as private land, in hopes of boosting productivity through increased investment and increased participation in land rental markets. This formalization appears to have increased land sales and rentals (Chamberlin and Ricker-Gilbert, 2016) and to have driven a transformation from what originated as informal arrangements of land borrowing between relatives to season-by-season formal rental agreements mostly between non-relatives. Our results call into question whether such reforms will result in the anticipated benefits not only in terms of efficiency, but also in terms of distribution. For example, reforms might increase

[29]Social structures can alter opportunities and enhance productivity by providing insurance, credit and information (Fafchamps, 2011; Hong and Kacperczyk, 2009). However, the same structures can also constrain (Munshi, 2014) For instance, sharing norms within extended family networks in Africa have been shown to limit investment in education and business (Di Falco and Bulte, 2015; Cox and Fafchamps, 2007; Baland, Guirkinger, and Mali, 2011)

[30]This reform started in 2002 with the new land policy and the final reform took effect in 2018 (see Peters and Kambewa (2007) for a historical account; and Holden, Kaarhus, and Lunduka (2006)

social conflict centering around altered social norms or notions of 'original settlers' and 'strangers' (see Peters and Kambewa (2007)) if distributional concerns are not adequately addressed.[31]

Finally, interdisciplinary, academic research using methodologies that can further illuminate the nuance in such settings is essential (Pande and Udry, 2005; Bowles, 2016). As the operation of land markets can be articulated with greater clarity by participants, it may be possible for economists interested in policy experiments to consider nuanced and varied institutional designs that emerge from grassroots-level, anthropological research. The institutions we have in mind are ones in which a feedback loop is created between government institutions and local actors so that policy changes can improve the functioning of land markets in a manner consistent with locally desired outcomes in adaptive and incremental fashion (Andrews, Woolcock, and Pritchett, 2017).

[31] Takane (2008) documents some of these conflicts.

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List of Tables and Figures

Table 1: Household and field characteristics, summary statistics

Variables						
Panel 1 Baseline household characteristics						
	Full sample		Tenant household		Landlord household	
	Obs.	**Mean (s.d.)**	**Obs.**	**Mean (s.d.)**	**Obs.**	**Mean (s.d.)**
Sex of household head = 1 if male, 0 otherwise	2500	0.78 (0.41)	882	0.82 (0.38)	531	0.79 (0.41)
Age of household head	2500	42.22 (15.11)	882	39.33 (13.29)	531	43.78(14.74)
Years of education of household head	2500	4.67 (3.46)	881	4.86 (3.57)	531	4.58 (3.42)
Household size	2500	5.14 (2.17)	882	5.26 (2.17)	531	5.35 (2.13)
Ln (value of household asset)	2,281	10.10 (2.96)	778	9.99 (3.15)	412	10.08 (2.95)
	Round 2014			Round 2018		
	Obs.	**Mean**	**(S.d.)**	**Obs.**	**Mean**	**(S.d.)**
Panel 2 Household land ownership and rental market participation						
Land owned (acre)	2500	2.21	(2.10)	2500	2.02	(1.73)
Total number of fields per household (both cultivated and uncultivated)	2500	1.91	(1.04)	2500	1.92	(1.04)
Rented in land =1 if so; 0 otherwise	2500	0.15	(0.35)	2,500	0.15	(0.36)
Rented out land = 1 if so; 0 otherwise	-	NA	NA	2,500	0.05	(0.22)
Rented in and out land = 1 if so; 0 otherwise	-	NA	NA	2,500	0.06	(0.23)
Inequity aversion – tenant index	-	NA	NA	2,500	3.49	(1.62)
Inequity aversion – landlord index	-	NA	NA	2,500	0.44	(0.86)
Panel 3 Field characteristics						
Field size (farmer reported)	4,788	2.27	(2.50)	4,652	1.93	(1.69)
Field size (GPS measured)	-	NA	NA	489	1.45	(1.47)
Poor soil quality = 1, 0 otherwise	4,788	0.22	(0.42)	4,652	0.17	(0.38)
Average soil quality = 1, 0 otherwise	4,788	0.25	(0.44)	4,652	0.31	(0.46)
Good soil quality = 1, 0 otherwise	4,788	0.52	(0.50)	4,652	0.49	(0.50)
Walking distance to home (minutes)	4,783	23.87	(41.91)	-	NA	NA
Active carbon (mg/kg of soil)	521	427.88	(164.10)	571	350.87	(188.25)
Panel 4 Rental rates and other contractual details						
Per acre rental rate (actual, for rented-in field)	506	13, 238	(10,458)	521	20,255	(11,161)
Per acre rental rate (actual, for rented out fields)	-	NA	NA	121	17,829	(9174)
Fixed rent = 1, 0 otherwise	-	NA	NA	632	1.00	(0.00)
Rental period =1 yearly, 0 otherwise	-	NA	NA	632	0.19	(0.39)
When rent paid (before the season =1 if so; 0 otherwise	508	0.95	(0.21)	640	0.96	(0.20)
With whom is rental contract (someone in the village = 1 if so, 0 otherwise	NA	NA	NA	633	0.62	(0.49)
Per acre rental rate (hypothetical)*	3,939	13,238	(10458)	4,115	23,352	(12,899)

Notes: *hypothetical rental rate – "What would be the yearly rental value of this field?"

Table 2: Village-level characteristics, summary statistics

	Round 2014		Round 2018	
Variables	Mean	Std. dev.	Mean	Std. dev.
Community characteristics				
Number of individuals in the village	404.21	(391.78)	NA	NA
Number of households in the village	75.34	76.82	NA	NA
Share of village's population belonging to Chewa ethnic group	0.90	(0.16)	NA	NA
Number of organizations	1.74	(1.29)	NA	NA
Average members per organization	12.57	(13.53)	NA	NA
Gender composition (percentage male)	39.67	(9.47)	NA	NA
Presence of irrigation scheme in the village = 1, 0 otherwise	NA	NA	0.18	(0.38)
Does the average wealth of tenants exceed the average wealth of landlords = 1, 0 otherwise	NA	NA	0.58	0.50
Intra-cluster coefficient for the per acre rental rates	0.08	0.01	0.20	(0.02)
Share of villages with at least some rental activity in the past 10 years.			1.00	(0.00)
Market Access				
Distance to paved/all-weather road (km)	2.50	(4.90)	NA	NA
Distance to national highway (km)	7.60	(10.04)	NA	NA
Distance to closest place to buy farm inputs (km)	13.50	(10.39)	NA	NA
Distance to market where produce can be sold (km)	5.21	(8.01)	NA	NA
Distance to fruits markets (km)	3.10	(4.23)	NA	NA
Gender composition (percentage male)	39.67	(9.47)	NA	NA
Migration				
Increase in out-migration = 1, 0 otherwise	NA	NA	0.72	(0.45)
Increase in in-migration = 1, 0 otherwise	NA	NA	0.65	(0.48)
Net migration (out-migration - in-migration)	NA	NA	-0.07	(0.51)
Trust and willingness to help each other / Social norms				
Both groups voting for Option A =1, 0 otherwise	NA	NA	0.19	(0.39)
Both groups voting for Option B =1, 0 otherwise	NA	NA	0.37	(0.48)
One group voting for Option A and one group for Option B =1, 0 otherwise	NA	NA	0.44	(0.50)
Level of trust in the village (1 – 5 increasing order)	NA	NA	3.34	(0.95)
Willingness of members to help one another (1 – 5 in increasing order)	NA	NA	3.29	(1.04)
Willingness of members to make contributions for a common good (1 – 5 in increasing order)	NA	NA	3.69	(0.98)

Sample size (i.e., number of villages): 250.

Table 3: Structure and results of the modified dictator game

Round	Bundle A	Bundle B	Scenario	Percentage of groups that opt for Bundle A
1	(500 MK, 500 MK)	(1000 MK, 500 MK)	If the group decides on Bundle A, each person in both groups gets 500MK. If the group chooses Bundle B, each member of the group gets 1000MK while each member in the other group gets 500MK.	34.4
2	(500 MK, 500 MK)	(1000 MK, 500 MK)	If the group decides on Bundle A, each person in both groups gets 500MK. If the group chooses Bundle B, each member of your group gets 500MK while each member in the other group gets 1000MK.	67.4
3	(500 MK, 500 MK)	(1000 MK, 500 MK)	If the group decides on Bundle A, each person in both groups gets 500MK. If the group chooses Bundle B, members of one group gets 500MK each while members in the other group gets 1000MK. However, we don't know at this point which group will have its members receiving the 1000MK. This will be determined by a coin toss.	41.0

Table 4: Correlation between the strength of fairness norm and equity aversion

Variable	Strength of fairness norm
Inequity aversion – tenant index	0.0218
	(0.7317)
Inequity aversion – landlord index	0.1725
	(0.0062)
Only question 7*	0.1627
	(0.0100)

Note: p-values are reported in parenthesis. The strength of the fairness norm is measured by the percentage of participants in each village who voted for the equal distribution in Round 3 of the modified dictator game.

Question 7 is: *"Last year land rental rate was 15,000 Kwacha. One landlord is in urgent need of money. In order to find a tenant, he decides to rent his land at 13,000 Kwacha. In the following weeks the landlord decides to rent his remaining land at 15,000 Kwacha"

Table 5: Correlates of field rental rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	ln(per acre rental rate)	ln(per acre rental rate)	ln(per acre rental rate)	ln(per acre rental rate)	ln(per acre rental rate)	ln(per acre rental rate)	ln(per acre rental rate)	ln(per acre rental rate)
Field size (acres)					-0.200***	-0.139***	-0.174***	-0.137***
					(0.0137)	(0.0143)	(0.0139)	(0.0144)
Square of field size					0.00799***	0.00419**	0.00646***	0.00406**
					(0.00199)	(0.00197)	(0.00198)	(0.00197)
Soil with good fertility =1, 0 otherwise					0.0415***	0.0414***	0.0415***	0.0424***
					(0.0155)	(0.0155)	(0.0154)	(0.0156)
Fine textured soil =1, 0 otherwise					-0.00231	-0.00660	0.000966	-0.00594
					(0.0174)	(0.0177)	(0.0173)	(0.0178)
Eroded field = 1, 0 otherwise					-0.0148	-0.0310**	-0.0110	-0.0315**
					(0.0160)	(0.0157)	(0.0159)	(0.0158)
Distance to the field (km)					0.00116	-0.00598*	-0.00297	-0.00606*
					(0.00330)	(0.00339)	(0.00331)	(0.00341)
Inherited field = 1, 0 otherwise					0.0845***	0.0738***	0.0695***	0.0726***
					(0.0169)	(0.0169)	(0.0168)	(0.0170)
Distance to national highway			-0.00673***	0.00826			-0.00282***	0.0125
			(0.00105)	(0.0102)			(0.00101)	(0.00979)
Distance to input market			-0.00899***	-0.0148			-0.00625***	-0.0154
			(0.00103)	(0.0103)			(0.000984)	(0.00987)
Distance to output market			0.00159	0.156**			0.000307	0.124**
			(0.00110)	(0.0657)			(0.00104)	(0.0633)
Constant	9.904***	9.532***	10.05***	9.702***	10.14***	9.854***	10.21***	9.926***
	(0.00810)	(0.115)	(0.0130)	(0.348)	(0.0232)	(0.114)	(0.0245)	(0.336)
Village fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4,222	4,222	4,187	4,187	4,200	4,200	4,165	4,165
R-squared	0.000	0.241	0.061	0.240	0.147	0.303	0.166	0.301

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Village rental rate range and strength of fairness norm

	(1)	(2)
Variables	ln(range)	ln(range)
Strength of fairness norm	-0.00952***	-0.00815**
	(0.00353)	(0.00365)
ln(median rental rate)	1.505***	1.286***
	(0.140)	(0.159)
Village controls	No	Yes
Constant	-4.451***	-1.957
	(1.423)	(1.620)
Observations	250	232
R-squared	0.356	0.402

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Village controls include market access, population, migration, and controls accounting for potential non-linearity between rental rate range and the strength of fairness norms. Thus, we control for whether the two groups chose different options, or both voted for the unequal income distribution. We also control for the share of people who selected the equal income distribution in rounds 1 and 2 of the game.

Table 7: Village minimum and maximum rental rates and strength of fairness norm

	(1)	(2)	(3)	(4)
Variables	ln(minimum)	ln(minimum)	ln(maximum)	ln(maximum)
Strength of fairness norm	0.00366*	0.00250	-0.00422**	-0.00344**
	(0.00209)	(0.00216)	(0.00171)	(0.00174)
ln(median rental rate)	0.550***	0.547***	1.069***	0.948***
	(0.0829)	(0.0943)	(0.0678)	(0.0761)
Village controls	No	Yes	No	Yes
Constant	3.700***	3.817***	0.0482	1.441*
	(0.842)	(0.963)	(0.689)	(0.776)
Observations	250	232	250	232
R-squared	0.190	0.251	0.536	0.572

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Village controls include market access, population, migration, and controls accounting for potential non-linearity between rental rate range and the strength of fairness norms. Thus, we control for whether the two groups chose different options, or both voted for the unequal income distribution. We also control for the share of people who selected the equal income distribution in rounds 1 and 2 of the game.

Table 8: Village rental rate range, minimum, maximum, and ethnic concentration

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	ln(range)	ln(range)	ln(minimum)	ln(minimum)	ln(maximum)	ln(maximum)
Share of village's population	-0.395*	-0.170	-0.0415	-0.00401	-0.244**	-0.133
belonging to the Chewa ethnic group	(0.228)	(0.247)	(0.135)	(0.148)	(0.110)	(0.119)
ln(median rental rate)	1.473***	1.242***	0.576***	0.580***	1.057***	0.935***
	(0.137)	(0.156)	(0.0815)	(0.0929)	(0.0665)	(0.0748)
Constant	-4.400***	-1.868	3.659***	3.589***	0.132	1.500*
	(1.408)	(1.597)	(0.835)	(0.954)	(0.682)	(0.767)
Controls	No	Yes	No	Yes	No	Yes
Observations	249	231	249	231	249	231
R-squared	0.340	0.392	0.175	0.222	0.528	0.566

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Village controls include market access, population, and migration.

Table 9: Relationship between rented-in acreage and households' participation in the market and the strength of social norms

	(1)	(2)	(3)	(4)
Variables	Total acreage rented-in scaled by total acreage own (OLS)	Percentage of households who participated in the market in 2018 (either as tenant or landlord)	Percentage of households who participated in the market as tenants in the past 10 years	Percentage of households who participated in the market as landlords in the past 10 years
Strength of fairness norm	0.00144	0.0450	0.133	-0.287**
	(0.000998)	(0.0919)	(0.123)	(0.122)
ln(median)	-0.0686	-5.765	14.58**	0.982
	(0.0462)	(4.270)	(5.702)	(5.662)
Constant	0.704	76.16*	-104.1*	29.40
	(0.471)	(43.53)	(58.14)	(57.67)
Observations	169	168	168	168

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Village controls include market access, population, migration, and controls accounting for potential non-linearity between rental rate range and the strength of fairness norms. Thus, we control for whether the two groups chose different options, or both voted for the unequal income distribution. We also control for share of people who voted for the equal income distribution in rounds 1 and 2. Results reported in Column (1) is an OLS specification, while Columns (2), (3), and (4) report the results of Tobit estimations to take into account censoring at 0 and 100.

Table 10: Results of t-test comparing quality of rented-in fields and owned fields

Soil quality variable	Own field Mean (s.e)	Rented-in field Mean (s.e)	Diff (s.e)	p-value
Measured active carbon	431.40 (8.010)	370.77(41.940)	60.632(42.697)	0.168
Fine textured soil = 1, 0 otherwise	0.246 (0.007)	0.269 (0.020)	-0.022 (0.021)	0.279
Soil with good fertility = 1, 0 otherwise	0.501 (0.008)	0.430 (0.022)	0.071(0.023)	0.002
Soil with any form of degradation = 1, 0 otherwise	0.547(0.008)	0.505 (0.022)	0.042 (0.023)	0.071
Eroded soil = 1, 0 otherwise	0.363 (0.007)	0.296 (0.020)	0.068 (0.021)	0.001
Nutrient depleted soil = 1, 0 otherwise	0.338 (0.007)	0.324 (0.021)	0.014 (0.022)	0.511
Soil suffer from water logging = 1, 0 otherwise	0.137(0.005)	0.123 (0.014)	0.015 (0.015)	0.340
Soil suffer from salinity/acidity = 1, 0 otherwise	0.054 (0.003)	0.067 (0.011)	-0.013 (0.011)	0.249

Table 11: Relationship between the quality of rented-in fields and strength of social norm

	(1)	(2)	(3)	(4)
Variables	Percentage of rented-in fields eroded	Percentage of rented-in fields good fertility	Percentage of rented-in fields with fine textured soil	Percentage of rented-in fields with any form of degradation
Strength of fairness norm	0.0957	-0.779	-1.112	-0.512
	(0.671)	(0.707)	(0.743)	(0.727)
ln(median)	165.2***	-71.47**	-28.47	150.0***
	(34.55)	(33.64)	(34.18)	(36.52)
Constant	-1,642***	848.4**	346.7	-1,483***
	(351.9)	(342.8)	(348.3)	(370.3)
Observations	169	169	169	169

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Village controls include market access, population, migration, and controls accounting for potential non-linearity between rental rate range and the strength of fairness norms. Thus, we control for whether the two groups chose different options, or both voted for the unequal income distribution. We also control for share of people who voted for the equal income distribution in rounds 1 and 2. All regressions are weighted by the inverse of total number of rented-in fields. This table reports the results of Tobit estimations to take into account censoring at 0 and 100.

Table 12: Summary statistics of IHPS and rainfall data compiled.

Variables	IHPS 2010		IHPS 2013		IHPS 2016	
	Obs.	Mean(std.)	Obs.	Mean(std.)	Obs.	Mean(std.)
Field level						
Rental rate (MK per acre (scaled by farmer reported farmland size))	2202	4969(5473)	2601	6362 (6188)	2262	6996(7139)
Rental rate (MK per acre (scaled by GPS recorded farmland size))	2,079	5874(7258)	2468	8243(9435)	2159	9320(11713)
Ln (rental rate /farmer reported farmland size)	2202	8.15(0.84)	2601	8.44(0.78)	2262	8.53(0.79)
Household level						
Household average farm acreage (farmer reported)	1,304	1.95 (1.80)	1,556	1.89(2.12)	1,524	2.44(3.89)
Household average farm acreage (GPS reported)	1,304	1.65 (1.57)	1,556	1.62(2.08)	1,524	2.10(2.41)
Share of households who participated in the market as tenants	1,304	0.14 (0.34)	1,556	0.14(0.35)	1,524	0.14(0.35)
Community level						
Share of fields for food crops	101	0.75 (0.17)	101	0.74(0.18)	101	0.74(0.17)
Share of fields for cash crops	101	0.21 (0.16)	101	0.23(0.16)	101	0.17(0.14)
Negative rainfall shock lag 1 = 1, 0 otherwise	101	0.80 (0.40)	101	0.33(0.47)	101	0.51(0.50)
Positive rainfall shock lag 1 = 1, 0 otherwise	101	0.03 (0.17)	101	0.35(0.48)	101	0.09(0.28)
Negative rainfall shock lag 2 = 1, 0 otherwise	101	0.02 (0.14)	101	0.04(0.20)	101	0.02(0.15)
Positive rainfall shock lag 2=1, 0 otherwise	101	0.40 (0.49)	101	0.21(0.41)	101	0.12(0.33)

Source of data: Authors own calculation using Malawi's IHPS 2010, 2013, and 2016. Raw rainfall data were sourced from CHIRPS. NB: Rental rate question asked to the respondents reads: "If you were to rent out this [PLOT] today for 12 months, how much could you rent it for?". Rental rates are reported in 2010 Kwachas using Consumer price index (see World Bank Database, retrieved on April 19, 2021).

Table 13: Effect of rainfall shocks on rental rate

	(1)	(2)	(3)
Variables	ln (rental rate)	ln (rental rate)	ln (rental rate)
Negative rainfall shock in the previous season	0.069	0.076	0.039
	(0.048	(0.047)	(0.058)
Positive rainfall shock in the previous season	0.016	0.0092	0.0053
	(0.064)	(0.061)	(0.085)
Negative rainfall shock in the two seasons ago		0.074	0.111
		(0.055)	(0.100)
Positive rainfall shock in the two seasons ago		-0.026	-0.103
		(0.048)	(0.088)
Negative rainfall last season * Negative rainfall two seasons ago			-0.225*
			(0.133)
Positive rainfall last season * Negative rainfall two seasons ago			-0.088
			(0.124)
Negative rainfall last season * Positive rainfall two seasons ago			0.125
			(0.090)
Positive rainfall last season * Positive rainfall two seasons ago			0.031
			(0.149)
Dummy for IHPS Round 2	0.328***	0.327***	0.322***
	(0.0433)	(0.0443)	(0.0438)
Dummy for IHPS Round 3	0.409***	0.405***	0.402***
	(0.0418)	(0.0467)	(0.0482)
Constant	8.087***	8.091***	8.112***
	(0.042)	(0.053)	(0.062)
Observations	6,958	6,958	6,958
R-squared	0.042	0.043	0.044
Number of EAs	101	101	

Fixed effects regression results.Standard errors are reported in parentheses and *** p<0.01, ** p<0.05, * p<0.1. The regression uses log rental rates as dependent variables. Specifications (1) and (2) do not include rainfall shock interactions while specification (3) does include these interactions. Standard errors are clustered at the community level. Note that rental rate is scaled by farmer reported field size.

Table 14: Effect of rainfall shocks on rental rate

	Low norm	High norm
	(1)	(2)
VARIABLES	ln (rental rate)	ln (rental rate)
Negative rainfall shock in the previous season	-0.125**	0.0170
	(0.0611)	(0.0667)
Positive rainfall shock in the previous season	0.117	0.0289
	(0.120)	(0.123)
Constant	8.139***	7.989***
	(0.0550)	(0.0632)
Observations	8,125	8,433
R-squared	0.008	0.000

Fixed effects regression results.Standard errors are reported in parentheses and *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The regression uses log rental rates as dependent variables. Specifications (1) is for "Low norm" sub-sample while (2) is "High norm" sub-sample. Standard errors are clustered at the community level. Note that rental rate is scaled by farmer reported field size.

Table 15: Effects of rainfall shocks on crop production choice

	(1)	(2)
Variables	Share of fields under food crops cultivation	Share of fields under cash crops cultivation
Negative rainfall shock in the previous season	0.0123	0.0036
	(0.0211)	(0.0169)
Positive rainfall shock in the previous season	0.0033	0.0085
	(0.025)	(0.0200)
Negative rainfall shock in the two seasons ago	0.0538	-0.001
	(0.067)	(0.0530)
Positive rainfall shock in the two seasons ago	0.0625*	-0.0436*
	(0.032)	(0.026)
Negative rainfall last season * Negative rainfall two seasons ago	-0.0131	-0.127
	(0.132)	(0.104)
Positive rainfall last season*Negative rainfall two seasons ago	-0.0111	-0.0628
	(0.0887)	(0.0703)
Negative rainfall last season * Positive rainfall two seasons ago	-0.0698*	0.0649**
	(0.0382)	(0.0305)
Positive rainfall last season * Positive rainfall two seasons ago	-0.121*	0.099**
	(0.0623)	(0.0494)
ln(per kg price of maize)	0.205***	-0.185***
	(0.071)	(0.056)
Dummy for IHPS Round 2	-0.0963***	0.107***
	(0.033)	(0.027)
Dummy for IHPS Round 3	-0.0349****	0.003
	(0.0191)	(0.0151)
Constant	-0.0145	0.880***
	(0.265)	(0.211)
Observations	289	289
Number of EAs	101	101

Standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1. Regression uses Tobit specification to take into account the censored nature of the dependent variable between 0 and 1.

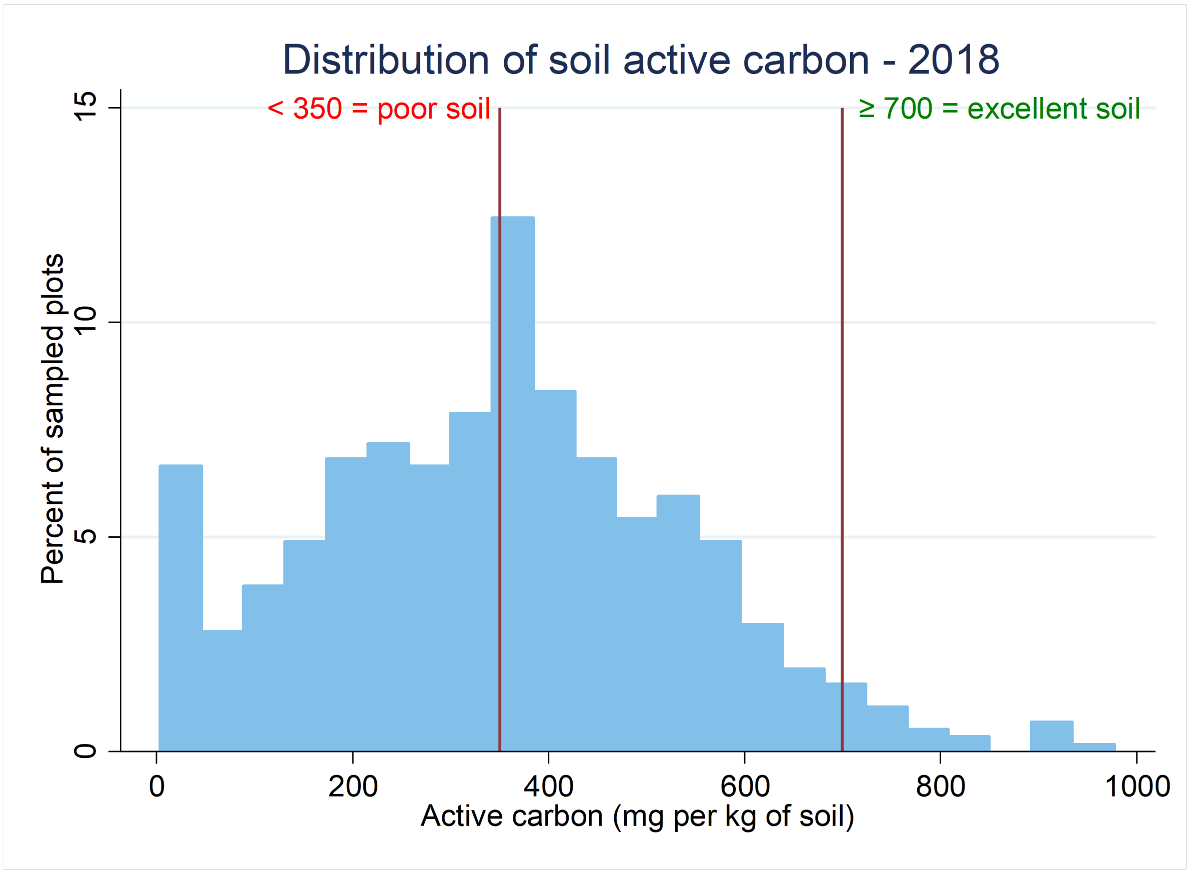

Figure 1: Distribution of soil active carbon (mg per kg of soil), a measure of soil fertility, in 2018

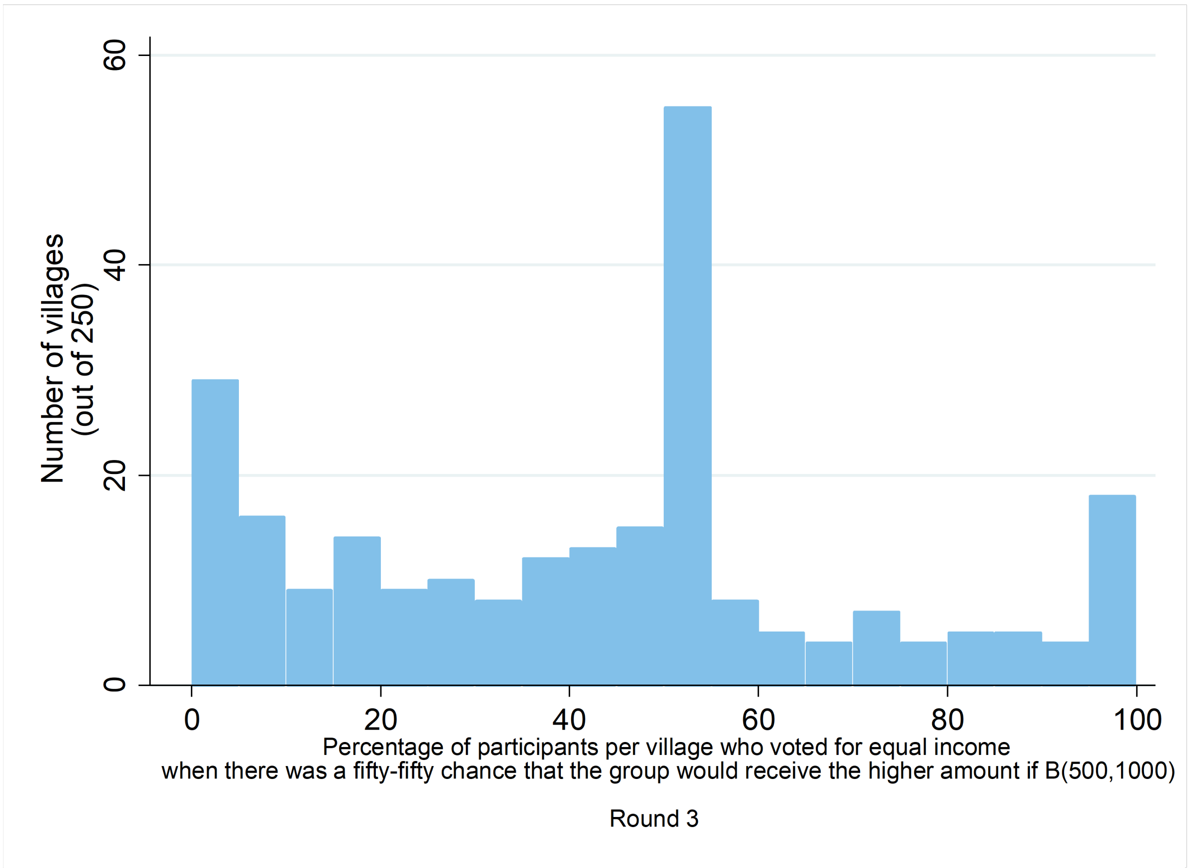

Figure 2: Distribution of percentage of participants per village that opted for Bundle A in round 3 of the modified dictator game

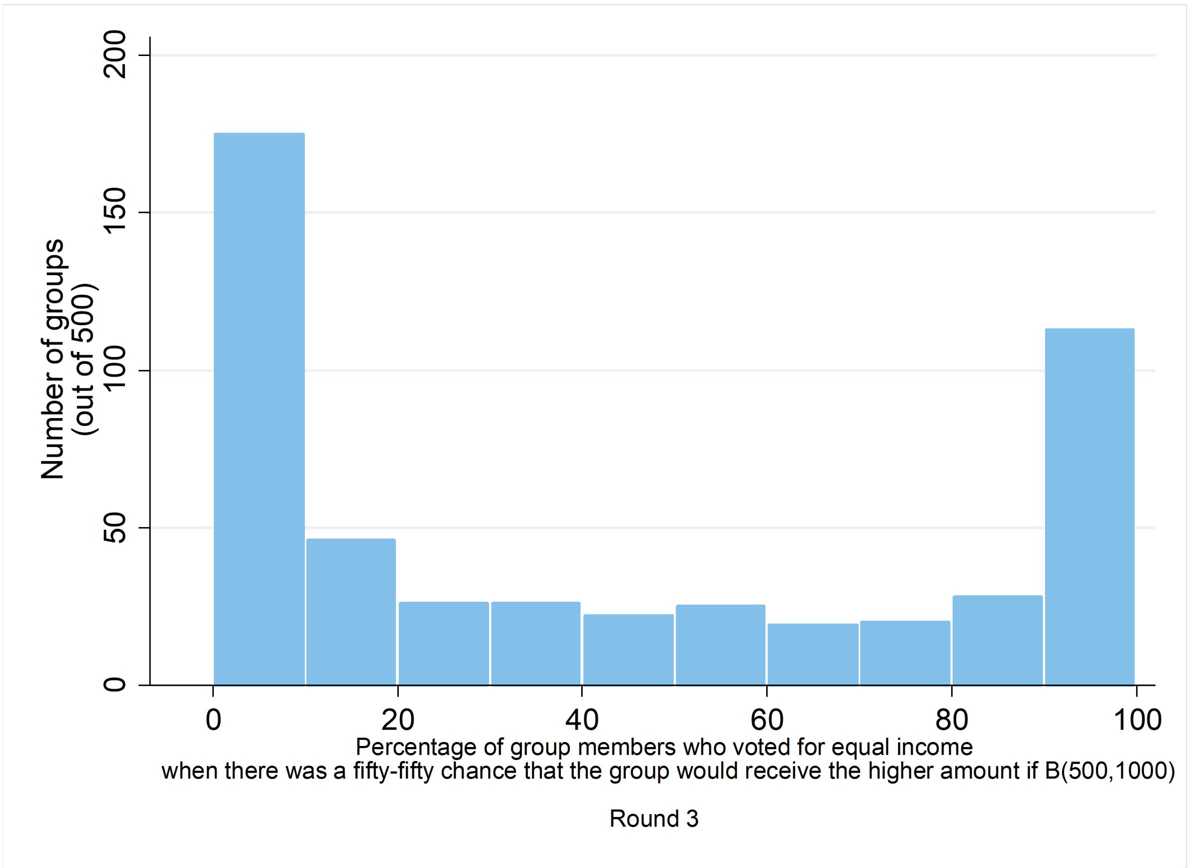

Figure 3: Distribution of percentage of participants per group that opted for Bundle A in round 3 of the modified dictator game

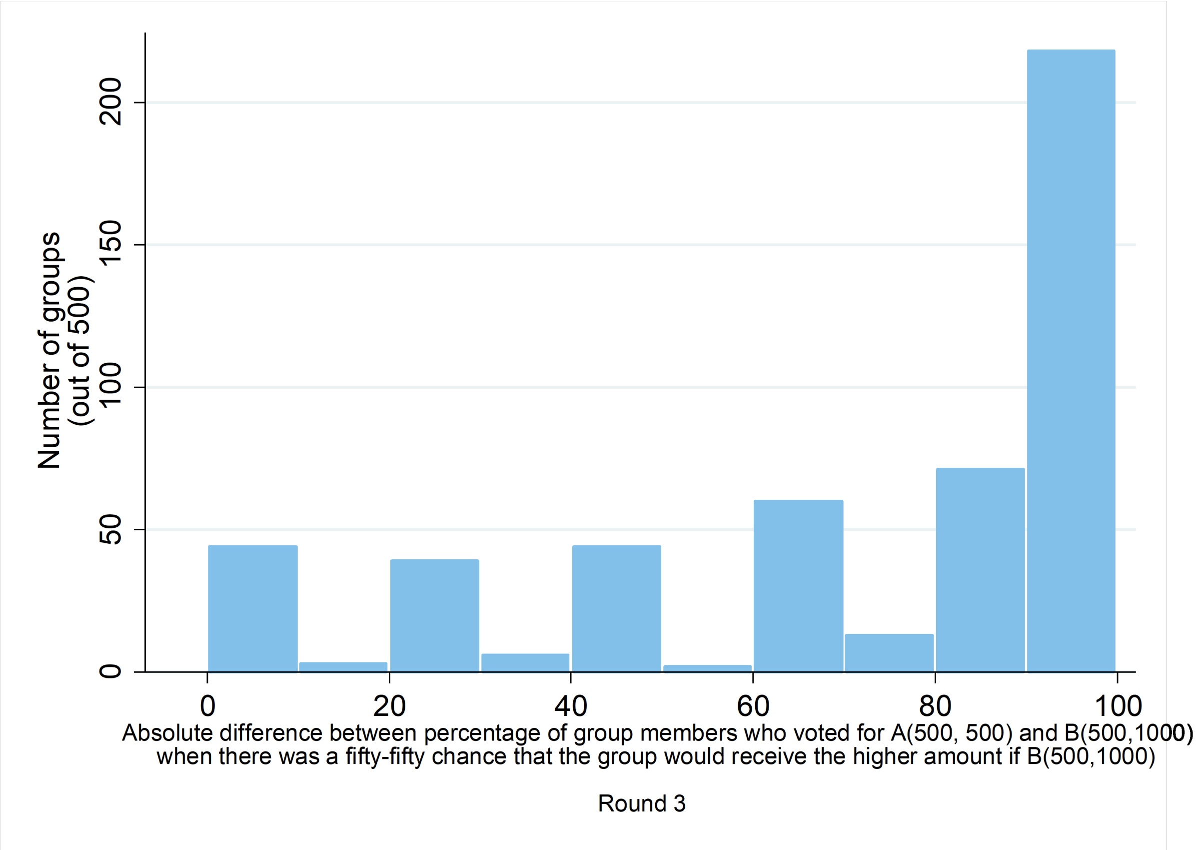

Figure 4: Distribution of the difference between percentage of participants per group that opted for Bundle A and Bundle B in round 3 of the modified dictator game

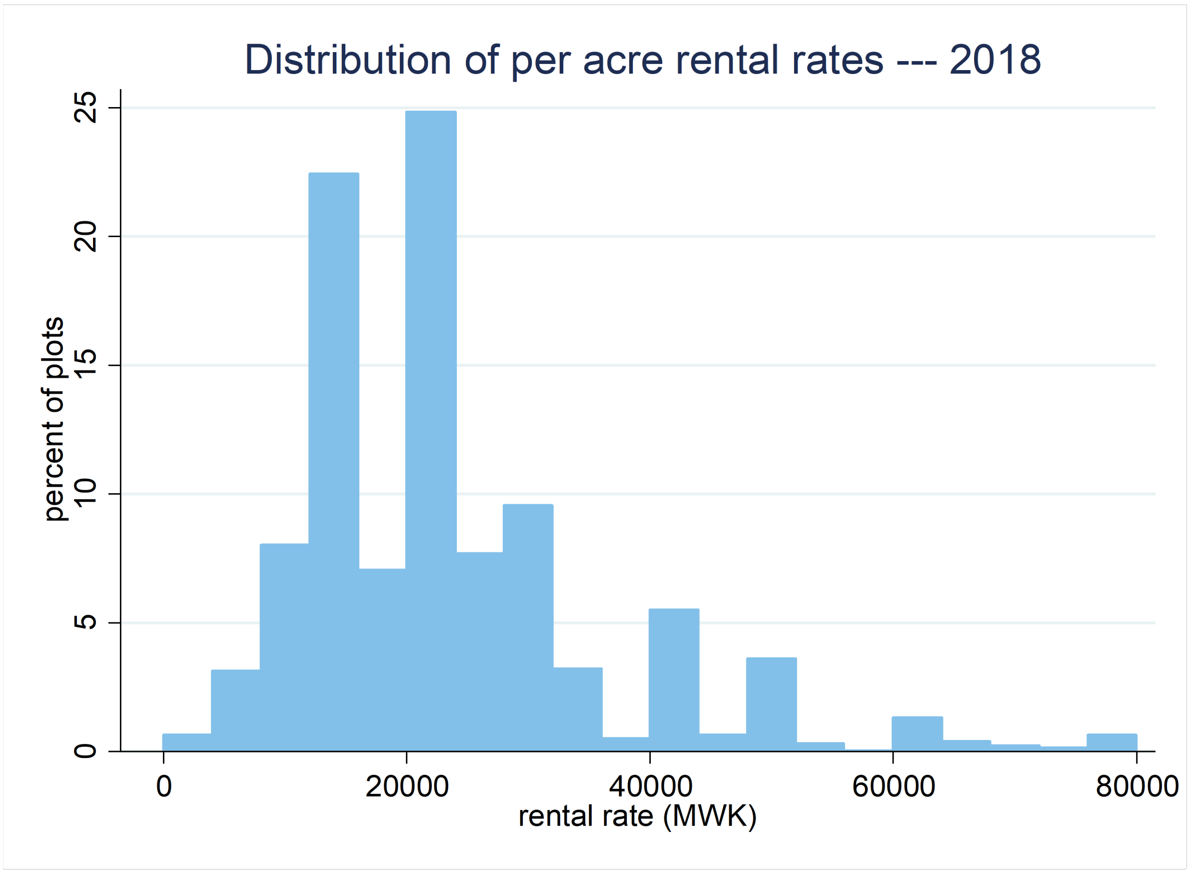

Figure 5: Distribution of per acre rental rate (all fields) (2018 survey round)

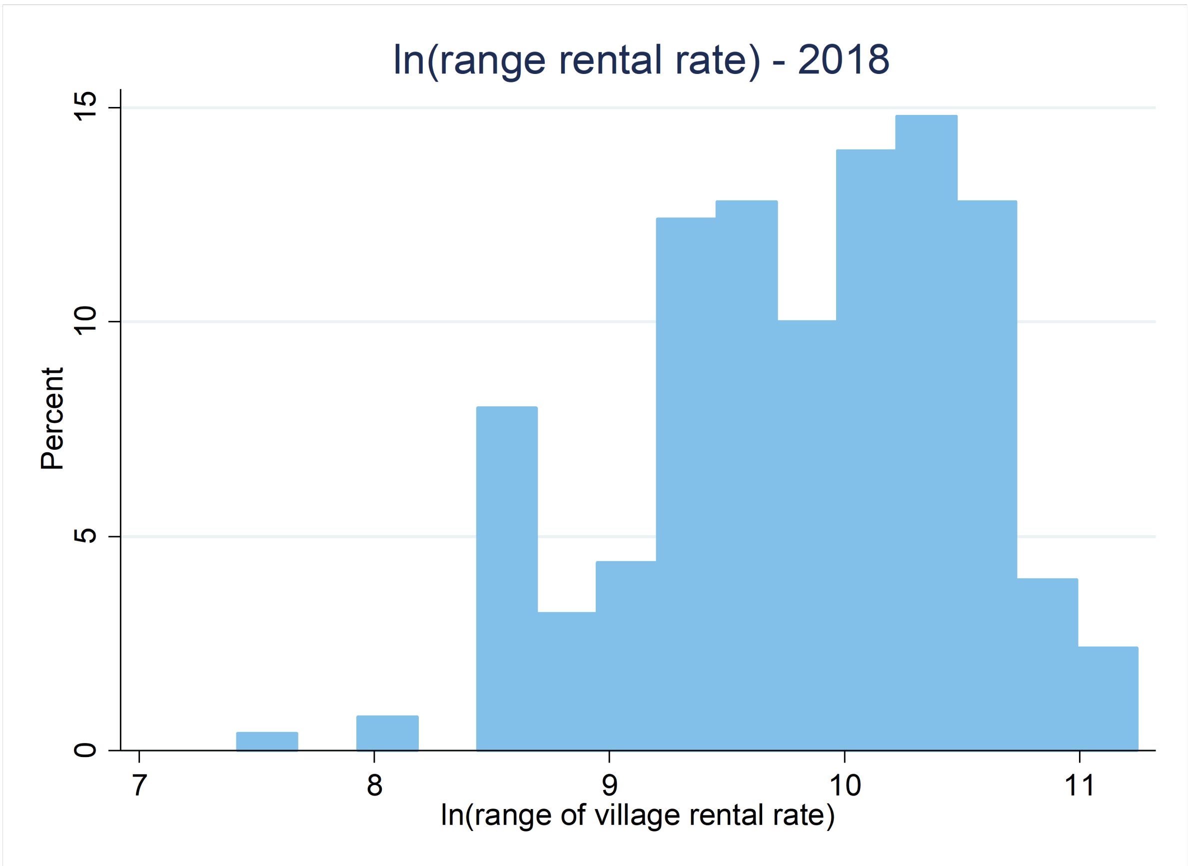

Figure 6: Distribution of hypothetical ln (village rental rate range) for 2018 survey round

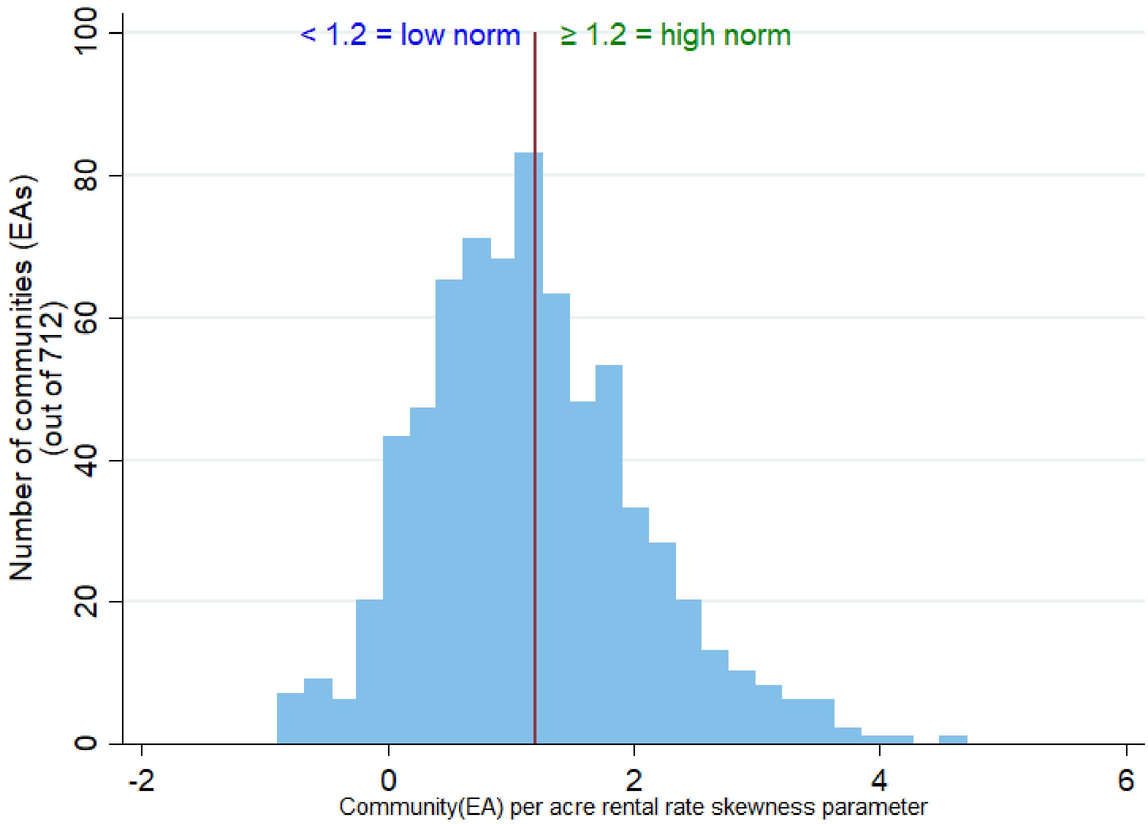

Figure 7: Distribution of community (EA) rental rate skewness parameters

A Appendix A

Table A.1: Inequity averse preferences: Proportion of respondents saying the scenario is "unfair" or "very unfair" by tenant and landlord households

Scenario	All	Tenants	Landlords	Protects whom if considered unfair
Panel A: Social determinants of rental rates				
1.Landowner, Yohane rents out an acre of land for 15,000 Kwacha. There is another landowner, Phiri in the village who rents out an acre of land for 17,000 Kwacha. A year later, Phiri sells his land and leaves the village for the city so that tenants can no longer rent from Phiri:				
A) ... After this, Yohane decides to rent out another acre to his regular tenant at 17,000 Kwacha.	0.78	0.78	0.76	tenant
B) ... After this, Yohane decides to rent out another acre of land to a tenant who used to rent from Phiri at 17,000 Kwacha.	0.55	0.53	0.51	tenant
C) .... After this, Yohane decides to rent out another acre to a tenant from another village who had just come to the village at 17,000 Kwacha.	0.63	0.62	0.58	tenant
2. A landowner usually rents out an acre of land for 15,000 Kwacha. His son becomes sick and the medical bills are very expensive. He increases the rent to 17,000 Kwacha.	0.64	0.66	0.59	tenant
3. A tenant rents in an acre of land from his landlord at 15,000 Kwacha. After this the tenant loses a family member and so needs money to support the funeral expenses, as a result the tenant is asking the landlord to reduce the rent to 13,000 Kwacha.	0.46	0.49	0.45	landlord
Panel B: Rental rate and shocks				
4. Last year the land rental rate was 15,000 Kwacha per acre. This year, there is a new buyer in the market for soy and tobacco, who is offering prices up to 15% higher compared to last year: Landlords increase this year's rent also with about 15%, from 15,000 Kwacha to 17,000 Kwacha.	0.58	0.59	0.60	tenant
5. Last year the land rental rate was 15,000 Kwacha per acre. This year, the main buyer announced that they still had many reserve and announced a decrease in minimum purchasing price of soy and tobacco, up to 15% less: Landlords reduce this year's rent, with about 15%, from 15,000 Kwacha to 13,000 Kwacha.	0.30	0.29	0.33	landlord
Panel C: Market Clearing Mechanisms				
6. Land available for renting is scarce, and 5 tenants want to rent a land. The landowner asks each of them to state the highest rent they are willing to pay, and then rents the land to the tenant with the highest rent.	0.73	0.72	0.73	tenant
7. Last year land rental rate was 15,000 Kwacha. One landlord is in urgent need of money. In order to find a tenant, he decides to rent his land at 13,000 Kwacha. In the following weeks the landlord decides to rent his remaining land at 15,000 Kwacha	0.64	0.64	0.60	landlord
8. Last year the rental rate was 15,000 Kwacha. This year there are more tenants seeking to rent land. One landlord decides to charge an increased rate, 17,000 Kwacha	0.65	0.68	0.60	tenant
Panel D: Fairness Norms				
9. The going rental rate is 15,000 Kwacha. There isn't much land available for rent and many tenants want the land. There is a poor tenant, Nyonga who desperately needs land to produce maize to feed his family. The landowner knows Nyonga's situation, and offers to rent to him at:				
A) ... 15,000 Kwacha	0.53	0.53	0.51	tenant
B) ... 17,000 Kwacha	0.90	0.92	0.85	tenant

Table A.2: Correlation matrix for inequity averse preferences scenarios reported in

	1A	**1B**	**1C**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9A**
1B	0.43 (0.00)										
1C	0.38 (0.00)	0.43 (0.00)									
2	0.16 (0.00)	0.10 (0.00)	0.05 (0.01)								
3	0.03 (0.14)	0.06 (0.00)	0.039 (0.05)	0.30 (0.00)							
4	0.17 (0.00)	0.12 (0.00)	0.07 (0.00)	0.16 (0.00)	-0.03 (0.09)						
5	-0.06 (0.00)	0.08 (0.00)	0.08 (0.00)	-0.09 (0.00)	0.09 (0.00)	-0.06 (0.00)					
6	0.22 (0.00)	0.11 (0.00)	0.12 (0.00)	0.19 (0.00)	0.01 (0.49)	0.12 (0.00)	-0.10 (0.00)				
7	0.07 (0.00)	0.09 (0.00)	0.10 (0.00)	0.14 (0.00)	0.12 (0.00)	-0.01 (0.62)	0.03 (0.18)	0.15 (0.00)			
8	0.27 (0.00)	0.18 (0.00)	0.20 (0.00)	0.19 (0.00)	0.08 (0.00)	0.25 (0.00)	-0.08 (0.00)	0.27 (0.00)	0.21 (0.00)		
9A	0.12 (0.00)	0.15 (0.00)	0.11 (0.00)	0.11 (0.00)	0.06 (0.00)	0.15 (0.00)	0.01 (0.57)	0.14 (0.00)	0.00 (0.99)	0.14 (0.00)	
9B	0.09 (0.00)	0.02 (0.31)	0.07 (0.00)	0.07 (0.00)	0.01 (0.48)	0.14 (0.00)	-0.07 (0.00)	0.17 (0.00)	0.10 (0.00)	0.16 (0.00)	0.31 (0.00)

p-values in parentheses

Table A.3: Fairness norm and rental rate variance

	(1)	(2)	(3)	(4)
VARIABLES	ln(variance of rent)	ln(variance of rent)	absolute skewness of rent	absolute skewness of rent
Strength of fairness norm	-0.0166**	-0.0138*	0.000508	0.000947
	(0.00641)	(0.00673)	(0.00341)	(0.00338)
ln(median rental rate)	2.962***	2.597***		-0.351**
	(0.255)	(0.294)		(0.147)
Village controls	No	Yes	Yes	Yes
Constant	-10.89***	-6.732**	0.770***	4.288***
	(2.588)	(2.998)	(0.280)	(1.504)
Observations	250	232	232	232
R-squared	0.389	0.420	0.023	0.047

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Village controls include market access, population, migration, and controls accounting for potential non-linearity between rental rate range and the strength of fairness norms. Thus, we control for whether the two groups chose different options, or both voted for the unequal income distribution. We also control for the share of people who selected the equal income distribution in rounds 1 and 2 of the game.

Table A.4: Effect of rainfall shocks on rental rate (rental rate scaled by GPS reported)

VARIABLES	Dependent variable: ln (per acre rental rate)		
	(4)	(5)	(6)
Negative rainfall shock in the previous season	-0.015	-0.015	-0.012
	(0.046)	(0.046)	(0.065)
Positive rainfall shock in the previous season	-0.030	-0.032	0.007
	(0.069)	(0.072)	(0.091)
Negative rainfall shock in the two seasons ago		-0.008	0.049
		(0.089)	(0.102)
Positive rainfall shock in the two seasons ago		-0.010	0.007
		(0.056)	(0.120)
Negative rainfall last season * Negative rainfall two seasons ago			-0.268**
			(0.127)
Positive rainfall last season * Negative rainfall two seasons ago			-0.083
			(0.191)
Negative rainfall last season * Positive rainfall two seasons ago			0.009
			(0.125)
Positive rainfall last season * Positive rainfall two seasons ago			-0.159
			(0.172)
Dummy for IHPS Round 2	0.362***	0.361***	0.367***
	(0.046)	(0.045)	(0.048)
Dummy for IHPS Round 3	0.418***	0.415***	0.430***
	(0.042)	(0.043)	(0.045)
Constant	8.278***	8.283***	8.266***
	(0.042)	(0.051)	(0.065)
Observations	6,636	6,636	6,636
R-squared	0.045	0.045	0.046
Number of ea_id	100	100	100

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Figure A.1: Histograms of within village per acre rental rate of nine villages with 18 or more fields (2018 survey round)

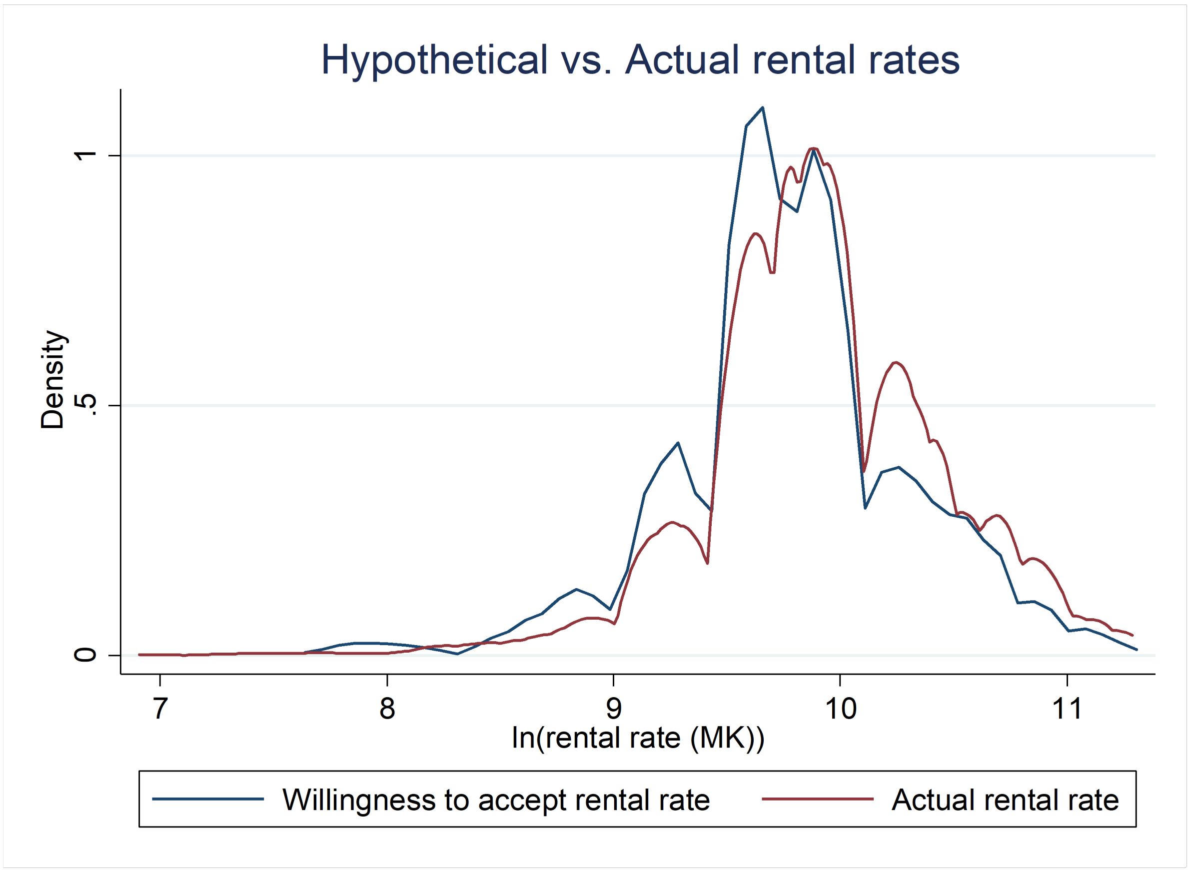

Figure A.2: Hypothetical vs. actual rental rate distributions for the 2018 survey round

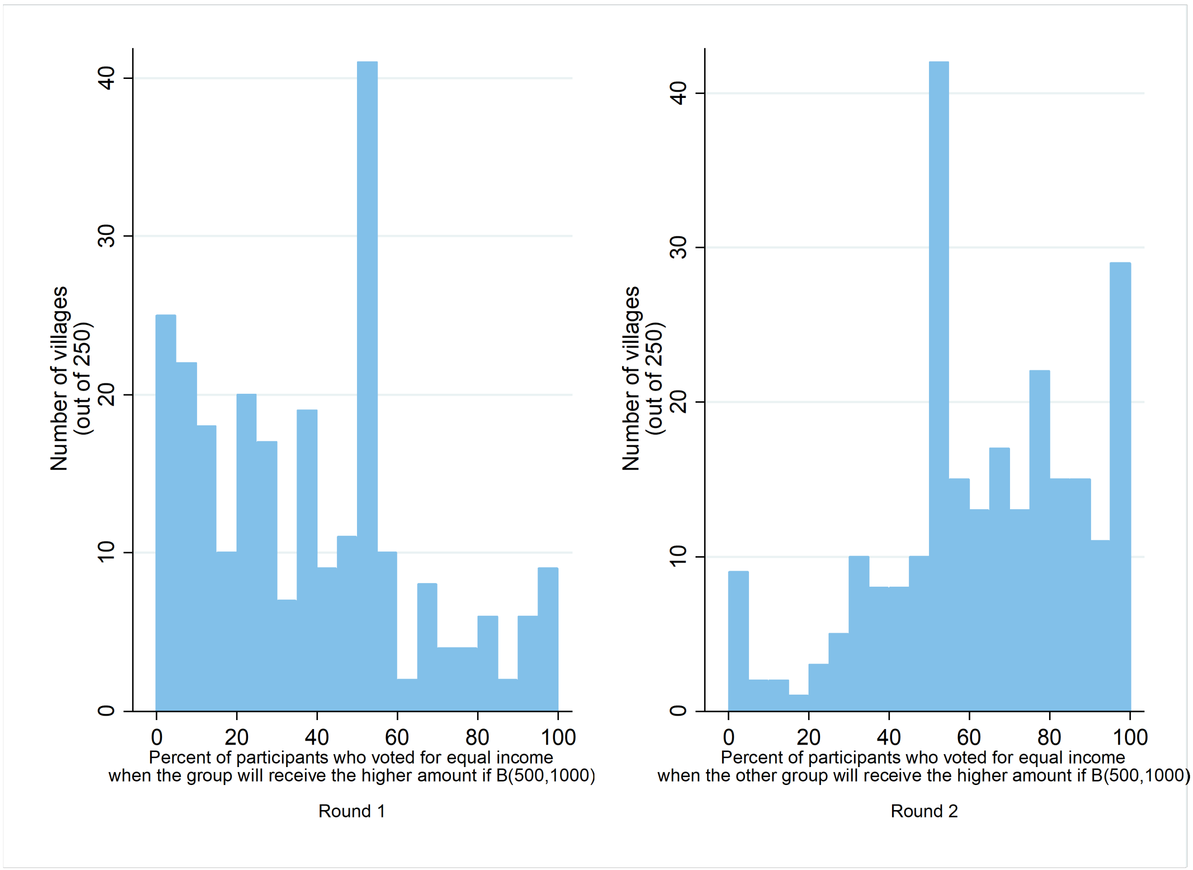

Figure A.3: Distribution of percentage of participants per village that opted for Bundle A in rounds 2 and 3 of the modified dictator game

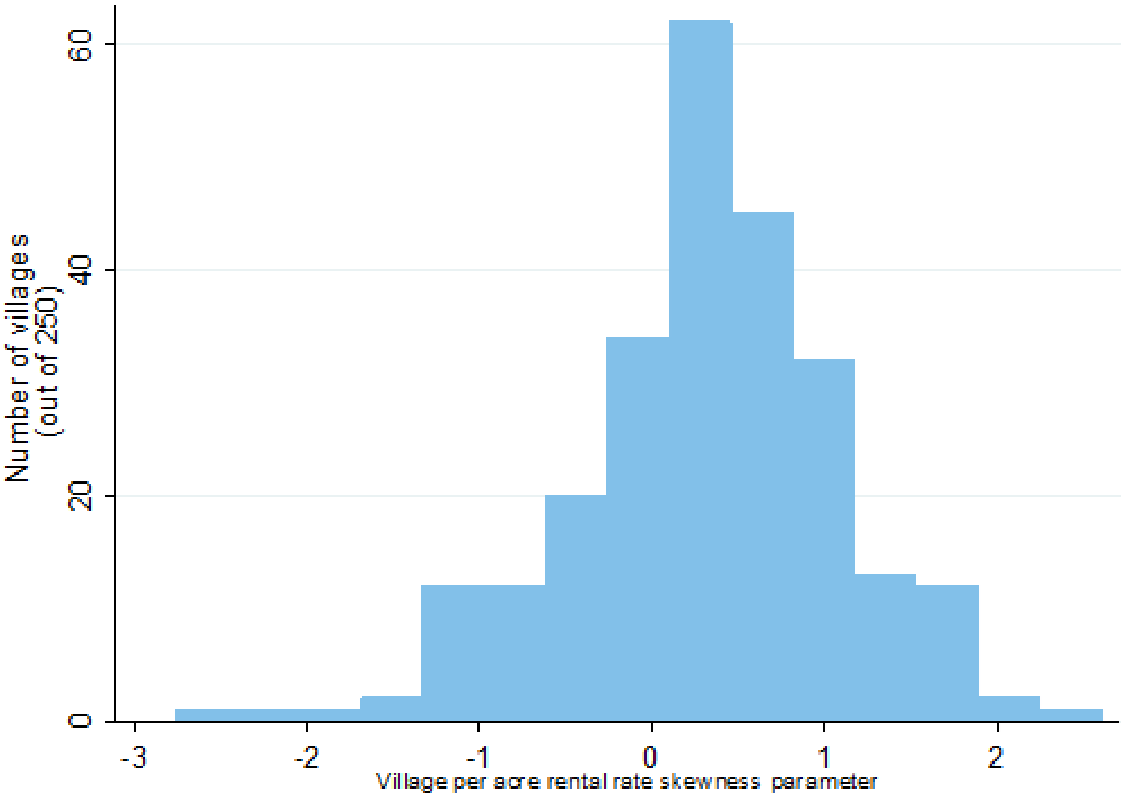

Figure A.4: Distribution of village rental rate skewness parameters.

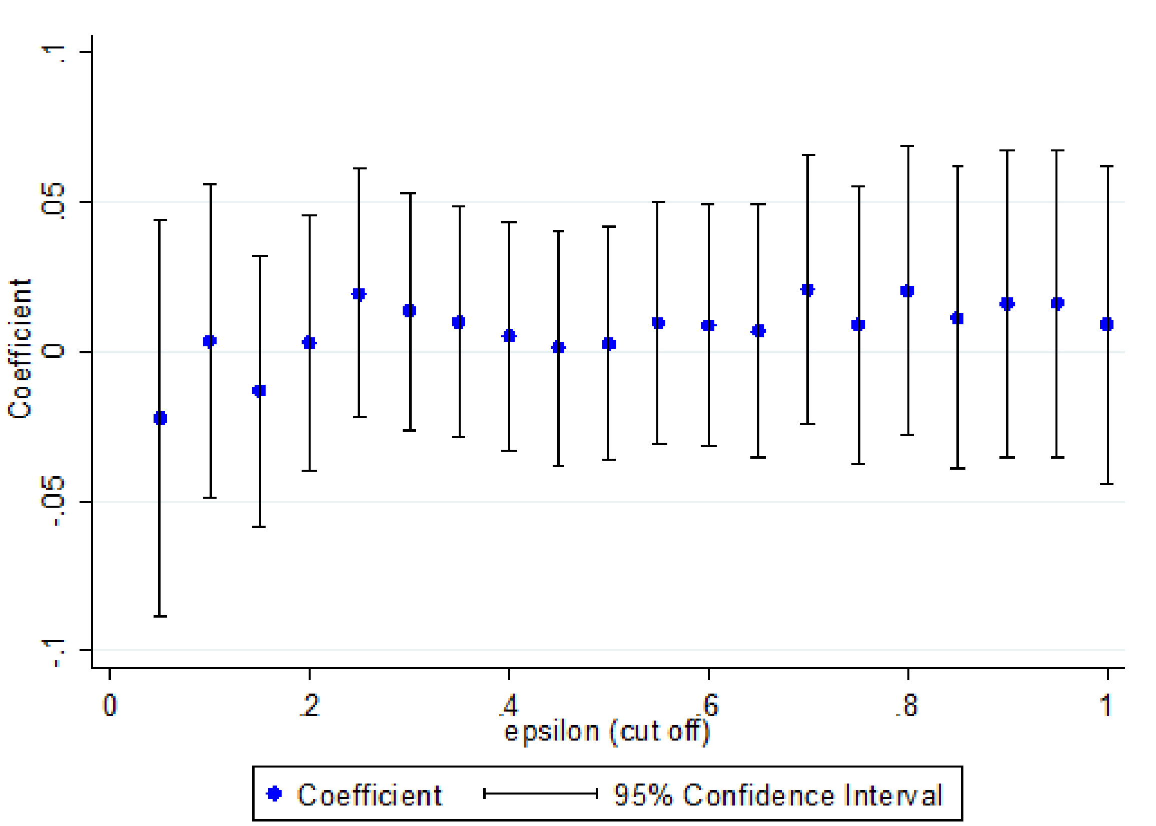

Figure A.5: A chart showing between the coefficients of the relationship between strength of fairness norm and the degree of bunching at varying values of epsilon. Note that epsilon denotes how far the skewness parameter is away from zero, either to the left or right. The higher the value of epsilon, the higher the bunching (i.e. high norm))

B Appendix B: MODIFIED DICTATOR GAME INSTRUCTION

Structure of the game

Arrange to meet 22 village members to one central village location, secluded from the rest of the village as to avoid bystanders. We suggest the following selection process: Ask all interested participants to come. Select all sample households first (one member per household, if more than one shows up, select the member randomly). For the remaining 12, select them at random from the remaining candidates.

Read from the following script: Good morning, I am [your name] and I came to this village to learn more about your village today. Ask whether anyone would like to say a prayer, if appropriate, and continue: I would like to do a group activity with you. This activity will take about 30 minutes. However, before we get started, let us introduce ourselves. Ask every individual to introduce themselves to the group by name.

Continue with the script. In this activity, I am going to put you into two groups: GROUP 1 and GROUP 2. Now divide the 22 participants in groups by letting each person draw a number one or two from a bag. Once the number is drawn, ask the individual for their name, (gender – this is visible), age, and acreage owned. Also, make sure to indicate the household IDs for those households who are in the sample. Then, place the participants in two groups. They cannot be visually in sight of one another or cannot be within audible range of one another. Make sure that the number of farmers in a group is not even, so that the possibility of votes tie is ruled out.

Continue with the script. Now, ask each group to make some decisions. Each group would be asked to choose between two Kwacha money Bundles: BUNDLE A (500MK, 500MK) and BUNDLE B (500MK, 1000MK). In Bundle A all participants would get 500 MK. In Bundle B some people would get 500 MK and others would get 1000 MK. It will soon become clear who will get what in that Bundle. To facilitate the decision-making process, you have two colored cards/chips (i.e. a BLUE card and a RED card): The BLUE card will represent a vote for BUNDLE A (500MK, 1000MK) and RED represent a vote for BUNDLE B (500MK, 1000MK).

Note for enumerator: Make sure you have enough of these BLUE and RED cards so that each participant has at least 3 pairs of the cards to play all three rounds of the game with. Let the participants rely on these cards in making their decision regarding their preferred Bundle. To guide the vote collection process, have two sacks/boxes one for each group. This sack/box would be used for collecting participants' votes.

After every round of play empty the sacks/boxes and store the votes (i.e. the cards) in separate bags for the two groups.

Note for enumerator: Continue with the script. We will be playing three rounds of the game. However, what you will be paid out will be based on one of the rounds only which would be selected randomly at the end. Each round has an equal chance of being selected, so think very carefully about your answers. Now, approach each group one by one, starting with Group 1, then Group 2, and ask each group to make a decision on round 1. Do not inform either group what they decided until you have completed all three rounds.

Round 1

Read this script: There are two Bundles; **BUNDLES A and B** for each participant in the group to choose from. Although you would be making individual decisions, the decision of the group will be determined by a simple majority votes. Depending on the choice that your group makes, every member in your group and the other group will get some Kwacha money. In this Round, if your group decides on Bundle A, each person in both groups gets 500MK. However, if your group chooses Bundle B, each member of your group gets 1000MK while each member in the other group gets 500MK. You have a few minutes to discuss these options.

BUNDLE A		BUNDLE B
(500MK, 500MK)		(500MK, 1000MK)

Now having explained this to them, and showing them **BUNDLES A and B**, let them use the BLUE and RED cards to make their decisions by dropping either a BLUE or a RED card in the sack/box designated for his/her group. A BLUE card will represent a vote for BUNDLE A and a RED card a vote for BUNDLE B. Note that the voting process is confidential: The participants should not see each-others' vote(s) nor the number remaining cards to use voting in the remaining rounds. Hidden from the participants' view, count the cards in each sack/box and note down the choices of the two groups for Round 1.

Round 2

Read this script: There are two Bundles; **BUNDLES A and B** for each participant in the group to choose from. Although you would be making individual decisions, the decision of the group will again be determined by a simple majority votes. Depending on the choice that your group makes, every member in your group and the other group will get some Kwacha money. In this Round, if your group decides on Bundle A, each person in both groups gets 500MK. However, if your group chooses Bundle B, each member of your group gets 500MK while each member in the other group gets 1000MK. You have a few minutes to discuss these options.

BUNDLE A		BUNDLE B
(500MK, 500MK)		(500MK, 1000MK)

Now having explained this to them, and showing them **BUNDLES A and B**, let them use the BLUE and RED cards to make their decisions by dropping either a BLUE or a RED card in the sack/box designated for his/her group. A BLUE card will represent a vote for BUNDLE A and a RED card a vote for BUNDLE B. Note that the voting process is confidential: The participants should not see other votes.

Hidden from the participants' view, count the cards in each sack/box and note down the choices of the two groups for Round 2.

Round 3 Read this script: There are again two Bundles; **BUNDLES A and B** for each participant in the group to choose from. Although you would be making individual decisions, the decision of the group will again be determined by a simple majority votes. Depending on the choice that your group makes, every member in your group and the other group will get some Kwacha money. In this Round, if your group decides on Bundle A, each person in both groups gets 500MK. However, if your group chooses Bundle B, members of one group gets 500MK each while members in the other group gets 1000MK. But we don't know at this point which group will have its members receiving the 1000MK. This will be determined by a coin toss. It could be members in your group or the other group. You have a few minutes to discuss these options.

BUNDLE A		BUNDLE B
(500MK, 500MK)		(500MK, 1000MK)

Now having explained this to them, and showing them **BUNDLES A and B**, let them use the BLUE and RED cards to make their decisions by dropping either a BLUE or a RED card in the sack/box for designated for his/her group. A BLUE card will represent a vote for BUNDLE A and RED card a vote for BUNDLE B. Note that the voting process is confidential: The participants should not see each-others' votes.

Hidden from the participants' view, count the cards in each sack/box and note down the choices of the two groups for Round 3.

Payoffs

At the end of Round 3, randomly pick 1 decision out of 6 using the following process: First select which one of the three rounds to use. You can use three pieces of paper which have Round 1, Round 2, and Round 3 on them. Mix them up in a container (in the presence of the farmers) and randomly select one.

Then toss a coin as to whose decision will be implemented – Group1 or Group 2. If the decision of the group whose decision was selected happens to be the unequal Bundle (i.e. BUNDLE B) and the Round is Round 3, toss another coin to decide which group gets the lower/higher amount.

Payment should be via envelops of which you should have plenty pre-prepared with both 500 MK and 1000 MK. In the case where everyone knows the group in which the other is, these can simply be handed out to the group quite easily.

Table B.1: Notation sheet

Number assigned for the game	Number assigned for the game	Group number	Name	Gender	Household ID (if available)	Age (years)	Education (years completed)	Land (acre owned)
Number assigned for the game								
1								
2								
3								
.								
.								
.								
.								
22								

Table B.2: Group Choices

	Group 1			Group 2		
	Votes for A	Votes for B	Who won (A or B)	Votes for A	Votes for B	Who won (A or B)
Round 1						
Round 2						
Round 3						

Which was the decision which was paid out? GROUP .... ROUND ....

C Appendix C: SOIL SAMPLING APPENDIX

For each field, we first recorded the cropping history and then asked the farmer to guide us to the field. After recording the GPS coordinates of the field in a central location and walking around the field to record the field area, we collected two soil samples at 0-20 cm soil depth. These samples were then mixed to make a composite sample. After collection, the soil samples are put in soil sampling bags and taken to the Bunda College Soil and Plant Analysis Laboratory for analysis. If the soils were wet upon arrival at the laboratory, the samples were first air dried. When dry, we sieved them through a 2mm sieve and recorded the soil texture using the hand feel method. We used SoilDoc to measure macronutrients, pH and soil organic carbon (Marenya and Barrett, 2009). See Weil and Gatere (2015) for an introduction to SoilDoc.

D Appendix D: IHPS

The IHS is a nationally representative cross-sectional survey implemented by the Government of Malawi through the National Statistical Office (http://www.nsomalawi.mw/) on a timely basis to provide vital statistics on agricultural production and economic outcomes such as poverty, food security, health, and education among others. The first IHS was conducted in 1997/98 while the third (i.e. IHS3) was conducted in 2009/10. The sampling frame of the IHS3 is based on the listing information and cartography from Malawi's 2008 Population and Housing Census (PHC). This includes the three major regions of the country, namely North, Center and South and stratified into urban and rural strata. The sampling design used for the IHS3 was a stratified two-stage, where in the first stage, the primary sampling units were enumeration areas (EAs) defined for the 2008 PHC. A total of 768 EAs were used for IHS3. In the second stage, a listing of households was conducted in each sample EA. A systematic random sampling technique was employed to select 16 primary households and five replacement households from the household listing for each sample EA (see "Third Integrated Household Survey (IHS3) 2010-2011: Basic Information Document" for a detailed sample design information). In 2010, a sub-sample of IHS3 EAs (i.e. 204 out of 768 EAs) were selected prior to the start of the IHS3 field work with the intention to track and resurvey these households in 2013, 2016, and beyond to study trends in poverty, socioeconomic, and changes in agricultural activities in Malawi over time. This sub-sample constitutes the IHPS. A detailed description and sampling procedure can be found at https://microdata.worldbank.org/index.php/catalog/2939/study-description